UNIVERSITY OF READING

Public policy decisions, match attendance and on-pitch performance in English football

PhD in Economics

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Abstract

This thesis consists of three Chapters on economic related outcomes related to English Association Football. We demonstrate that these outcomes are a result of policy decisions or strategic decision making by government, football clubs or sporting bodies and how they add to existing understanding within sports economics.

In Chapter one, we examine mass attendance events, which are a mainstay of economic and social activity. Whilst the benefits from such interactions are large, they may also facilitate the spread of diseases from person to person. We provide evidence on how mass outdoor gatherings contributed to the spread of Covid-19. We do this by considering how attendance at football matches in England in February and March 2020 contributed to Covid-19 cases and deaths in local areas in April 2020. We contribute to the literature on the Covid-19 pandemic and mass attendance events, policy areas that continue to be studied so that preparation can be made for future similar style events.

Our results suggest that an additional match taking place in an area in March increased Covid deaths by 2 or 3 per 100,000 people in that area. Overall, our analysis suggests that there should be caution in allowing fans to attend matches either during or immediately after a pandemic, despite the economic impact playing football behind closed doors has on clubs.

The second and third Chapters look at the effect of one specific change as an outcome influencer, either introducing a 3G pitch instead of a grass pitch, or where fans have taken over the ownership of a club instead of a single owner or company, this is then tested to see how this affects performance either financially or on the pitch. These two Chapters contribute to the growing football related sports economics literature, by exploring a unique dataset covering the entire grassroots non-league football structure in England, a part of football economics literature that has largely been untouched.

The policy interest in this section lies in whether and how far, sporting authorities should promote either these different types of football pitches or alternative models of ownership of clubs. There is wider football community interest in relation to the introduction of 3G pitches as they can be re-used during poor weather conditions, don't have to be relayed but also are an expensive initial outlay, so the benefits are worth investigating. These benefits are theorised to be either that the community re-use and availability during inclement weather is an attendance driver or whether the pitch itself gives a competitive advantage to the club using the pitch regularly, when compared to clubs that do not have them. Within the existing literature, Chapter Two uses competitive balance and uncertainty of outcome hypotheses (Humphreys and Zhou, 2015) as a theoretical background to test whether a football club installing a 3G pitch has an effect, if any, on attendance at matches or on-pitch performance by clubs. We find that 3G pitches appear to only affect attendance outcomes at the lowest competitive levels (Step 7 and below) and they do not appear to have significant on-pitch performance advantages (there could be some specific within Step-level effects at league level but these require future investigation).

Football clubs are also social enterprises with significant stakeholders, namely fans and supporters, who exert influence on outcomes often without having any formal decision-making authority. In Chapter Three, we test this question of fan involvement in football by looking at the effect of fan-ownership of clubs on attendance and performance. The positive effects of fan ownership are more evident in this Chapter, than the effects of a 3G pitch in Chapter Two. Fan-owned clubs when compared to clubs not owned by fans, have an average attendance increase in Steps 2, 3 and 5 of the non-league structure. Home club performance also improves with positive effects for fan-ownership, making home wins more likely at Steps at 2-7. We also find an increase in the number of goals scored per fan-owned club but only at Step 7. This may be reassuring to fan-owned clubs that they are not at a disadvantage in the lower levels of non-league football, and potentially influence football administrators to encourage this model, especially in light of government interest in greater regulation around football ownership.

Overall, the thesis sets out the policy area or club-level decision intervention in each Chapter, set within the different theoretical frameworks and shows some clear outcomes that may alter our assumptions around drivers of football attendance and football match outcomes.

Declaration of original authorship:

‘Declaration: I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.’

MATTHEW YEO

Contents

Introduction

This work is a series of three sports and health related economics papers, using unique datasets from English football, firstly linking data on football matches with Covid-19 data to each Local Authority area and then later using data on English non-league football structures and matches. By using these datasets we contribute to the growing football economics literature, particularly the literature on what determines attending a football match.

The dataset, used in the first Chapter, utilises the Covid-19 data with football attendances contributing to mass attendance event literature. The second dataset, used in Chapters two and three uses grassroots non-league data that covers the entire non-league English football structure and for the first time in this context, we are able to assess the effects of two different issues, the effect of a club having a 3G, artificial pitch and then later examining the effect of a non-league club being fan-owned, each separately on attendance and on-pitch performance. This takes us into an examination of grassroots football in England, an area that Economics has to yet to really explore, with each club in the dataset being a community asset that local people interact with on a daily or weekly basis making for a worthwhile economic unit to study. The two Chapters analysing non-league football also contribute specifically to literature on home advantage (Peel and Thomas, 1996) and uncertainty of outcome hypotheses (Humphreys and Zhou 2015) that are two of the main theories for determining football match attendance.

In March 2020, England was 'locked down' nationally and then re-opened only regionally only two months later, depending on how endemic the spread of Covid-19 had been in each region or nation.[1] Journalists and academics were questioning how and why it had occurred and also whether different policy decisions could have been made. We utilise a dataset that covers the 2019-2020 season, matching this data at the

[1] https://www.gov.uk/government/speeches/pm-address-to-the-nation-on-coronavirus-23-march-2020 UK Prime Minister statement on national Covid-19 situation (accessed 8/2/2024)

local council level area to data on Covid-19 cases, deaths and excess deaths. We then add to that demographic controls that relate to the local area (but collected nationally via the Census).[2]

In this Chapter, the policy outcome studied is that of whether allowing fans to continue attending matches up until a national 'lockdown', helped to spread Covid-19 in England and if instead, closing football stadiums earlier could have saved lives.[3] We find that there is some effect of the spread of Covid-19 at football matches and we link this to the local area where the match takes place. We accept that in our study there are some issues of endogeneity and unknown factors that could be influencing this outcome. For instance, there is an overspill issue, in that, we use each London authority as a separate one (there are 32) but a fan attending a match would travel much easier from some part of London in a short space of time that one travelling across more than one borough area elsewhere, thus making it easier for away fans to attend. One avenue we would have liked to explore further with this data was the return of English football in the Autumn of 2020 when Covid-19 vaccinations were still unavailable. However, whilst fans were allowed to return, they were simply not allowed to return in sufficient numbers in England for us to re-examine our theories. A German study (Fischer, 2021) was able to replicate the experiment to an extent but was able to do as German municipal areas and data collection is made at smaller levels than the UK and fans attended elite matches in much larger numbers. The problem also with later studies was that fans attending matches were both more aware of Covid-19 and took precautions (social distancing and only being in small groups) and that authorities enforced separation of fans.

In the second Chapter, we extend the non-league data part of the Covid-football dataset into the entire formal non-league football structure in England, to examine the

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[2] All demographic variables are from the Office for National Statistics

[3] This Chapter was written with two co-Authors (as listed in Chapter 1, Matthew Olczak and J. James Reade) and as a paper was published in Covid Economics (2020)[3]. The author of this thesis contributed to the strategy, writing, data replication, conclusion and also making sure the data from multiple sources matched at the local government area level (a task made more difficult by different areas changing in the two years the data collected was used).

effect of 3G (artificial) pitches on football match attendance and on-pitch match outcomes.

In this Chapter instead of looking at the effects of football attendance on a policy decision, we look at the effect of a policy potentially affecting attendance, or performance, allowing 3G pitches to be an option for clubs to choose to have. In football, on-pitch performance can be linked to financial stability. Poor performing clubs potentially see a loss of revenue through fans losing interest and that in 'open leagues', with promotion and relegation they can then also get relegated. A relegation to a lower division, can often mean suffering some loss of revenue, but it can sometimes give the club a chance to improve on-pitch results with playing against lower strength clubs and this is why we cover a range of seasons across 2011-23. In opposition to that, if a club is promoted, the results in the following season may well be worse, as they play against better clubs, they may however experience a rise in attendances. For these reasons, we use attendance at football matches across a range of seasons (from 2011-23) within a database of over 412,000 matches across the entire non-league network. This covers a range of 'Steps' from 1-13, although we mainly focus on those at steps 1-7 or 1-9 as these contain either the clubs that have 3G pitches or that are registered as fan-owned. Non-league football in England in 2022 is structured as per Table 1, below.

Table 1. Premier League, EFL and non-league structure in England, including Step description

Football League and non-league structure in England

- Premier League
- Championship
- League One
- League Two
- Step 1 (National League).
- Step 2 (National League North, National League South)
- Step 3 (Northern Premier League, Southern Premier League Central, Southern Premier League South, Isthmian League Premier Division
- Step 4 (Leagues split 'Division One', East, West, Central for North, South & Isthmian; the Isthmian League structure covers parts of London, South East & East England).
- Step 5 (Combined County level leagues – where a number of counties within a region are combined into a league)
- Step 6 (Second level of Combined County level leagues – with direct promotion and relegation between these leagues with Step 5 being the 'Premier' Combined County League)
- Step 7 ((A large number of Single County leagues (such as Oxfordshire, Nottinghamshire, etc), in areas with greater concentration of teams, some are still at wider regional level, such as 'Thames Valley Premier League', or 'Central Midlands League Division North).
- Step 8 -13 (These are Steps that vary area to area in terms of how many Steps there are and are very localised).

It is worth noting that a club could progress from one end of the structure to the other. In practice this would be extreme as clubs at the top level (Premier League) are often internationally renowned (and usually owned by very wealthy owners) and the level of investment involved would be extreme. Importantly though, clubs can be relegated and promoted from each league or once being relegated to the National League Structure in Step 1, the structure then becomes regional, with the National League splitting into two leagues within that Step, at Step 2, one being in the North of England and the other in the South. This then continues to split downwards until Step 7, increasing in the number of leagues within Step each time. It is important to note that, below Step 7 is often 'park' football, sparsely attended or attendance sometimes not officially recorded at all but although attendance data is inconsistent, match reports are still filed, with results, goals and other information recorded.[4]

This is a subject that has policy impact in more than one area. 3G (or very recently also, 4G) artificial pitches, can last for 3 years or more, are often a community resource (they are an expensive outlay and usually only available to lower-level clubs if they bid for Football Foundation grants) and thus shared with some nearby clubs but also hired out to the local community and then a valuable financial resource to the clubs. They are, however, controversial and an additional reason that motivates why we study them, is whether they give clubs an advantage on the pitch, no matter how small. The cost contrast is that they can have an environmental impact on the local area (by removing grass and creating additional water run-off elsewhere) and there is also a question around physical health and whether they can increase certain types of sports injuries, with each of these aspects briefly covered in the Chapter.[5] We acknowledge that the data itself contains some flaws that we recognise. There is clearly some endogeneity within regressions using Attendance or on-pitch performance related data and then in the same regression using other measures that rely on some of this data,

[4] https://footballfoundation.org.uk/3g-pitch-register (accessed 8/2/2024)
[5] *This Chapter as with Chapter 3, was written by me, with data obtained by J.James Reade obtained originally from The Football Foundation and from the website Non-League Matters which we acknowledge in Chapter 2.

such as the goal difference between clubs, or the Elo rating which ranks clubs based on previous results. We try to address this through robustness checks such as attempting to test against the 'uncertainty of outcome' hypothesis (Humphreys and Zhou 2015) but also have to accept that other unknown factors could be affecting results. We are also reliant on how accurately the data is recorded and it is acknowledged that, professional and part-time clubs located at the higher Steps would have better facilities for accurately recording attendance for instance than amateur clubs at say Step 7 or below.

The third Chapter utilises the same non-league data as Chapter Two, only in this case, we examine the impact of Community Ownership, or 'fan-owned' football clubs on financial and on-pitch performance. Ownership of football is an interesting topic for analysis; the sports economics literature has long recognised that sports club owners will often win (or utility) maximise rather than profit maximise, and this choice of ownership objective can often contrast with the major stakeholders in sports clubs - the fans, or members. Community Ownership gives fans a level of democratic, usually direct involvement, in the strategic management of the club, it also spreads the financial and potential mis-management risk that comes from whoever as an individual might own the club as an alternative.

Similarly, to the second Chapter, we examine club financial performance through the use of attendance data as a proxy for revenue and on-pitch performance through a range of metrics, using home and away goals, goal difference and match outcomes such as wins or losses.

There are fewer Community Owned clubs across the non-league structure when compared to those with 3G pitches (There are 43 clubs with this giving us over 8000 matches, or just below 2% of the overall match data contains a fan-owned club).[6]

[6] https://thefsa.org.uk/news/community-owned-clubs-directory-launched/ a current list of fan-owned clubs is the basis of our study, we expanded this through historical research to include those clubs that were fan-owned and then subsequently the fans sold their shares to another owner. The list shown also will potentially include newly made 'fan-owned' clubs that are not included (accessed 8/2/2024)

Ownership of football clubs is currently one of the higher profile issues within English football in particular, with teams like Reading FC, struggling with owners that have been fined by HMRC and deducted points[7]. The previous and current government both have committed to an independent football regulator.[8] Our motivation in examining this issue of fan-ownership comes from also wanting to establish whether non-profit models are viable utility maximisers when competing against other more traditional models of ownership that assume a single owner. We use data from the Football Supporters Association that accredits clubs that are wholly or at least 50% fan owned. The purpose of this is to distinguish between clubs that are owned by community trusts, with small fan (or even token) amounts of ownership or consultation.

From a results perspective, we find that the impact of community ownership is of some value to clubs at the lower end of the non-league structure, with the apparent benefit to fan-ownership tailing off at Step 4. There is also a positive benefit for clubs at Steps 2 and 3 when compared to non-fan owned clubs. This though appears to be the main peak as, although there are some famous exceptions (such as Exeter City and AFC Wimbledon) these are not included in our database as their success was earlier and the National League, at Step 1 (the top non-league) has a number of clubs than can have 1000's of fans attending, full-time squads and for many a rich history of English Football League(EFL) success.

Despite the apparent greater financial resource and often legacy support for higher ranked clubs, there does appear to be some merit to fan-ownership. We find that fan-owned clubs in non-league football in England have some advantages in terms of home wins over the period studied, to the degree of between 2-5% depending on whether the club is in either Steps 2-3 or Steps 5-7. In addition, clubs playing at Steps 2, 3 and 5,

[7] https://www.bbc.co.uk/sport/football/66031836 (accessed 16/9/24) Reading FC received a 'winding up' petition from HMRC on more than one occasion and were deducted points as a result.
[8] https://lordslibrary.parliament.uk/research-briefings/lln-2024-0029/
(accessed 16/9/24) Labour committed to an independent football regulator in the King's Speech to examine football ownership.

have an advantage of between a 10-30% increase in home attendance if they are fan-owned.

Chapter 1: Mass Outdoor Events and the Spread of a Virus: English Football and Covid-19[9]

Matthew Olczak J.James Reade Matthew Yeo

[9] This is an adapted version of a paper published in Covid Economics – Issue 47 (https://cepr.org/publications/covid-economics-issue-47) With the co-authors listed in the Title page to this Chapter.

1.1. Introduction

Mass gatherings such as work meetings and conferences, and leisure activities such as music concerts and sporting events are a mainstay of economic activity.[10] Whilst the benefits from such interactions are large, there are also costs. The events themselves may be dangerous for participants, or observers, or they may facilitate the spread of diseases from person to person. As the Covid-19 pandemic developed in 2020 these trade-offs came to the forefront. Around the world, restrictions were put in place to prevent mass gatherings as the risk of the disease spreading and the resulting impact on public health infrastructure was judged to be too severe.

In order to understand the benefits such restrictions can have and when they should be relaxed, evidence is needed on how mass gatherings contributed to the spread of Covid-19. An important contribution is Ahammer et al, who show that indoor sports events appeared to increase the spread of the virus in the US (Ahammer et al., 2020). In addition, there are a few studies that show how outdoor events contributed to the spread of influenza in the US. However, we are aware of only one existing study that considers the impact of mass outdoor events outside the US on the spread of previous viruses or Covid-19, namely who looks at football matches in Germany in the Autumn of 2020. As Sassano et al, note, this is a `surprising gap' in our knowledge (Sassano et al., 2020). The aim of this Chapter is to address this gap by considering how attendance at football matches in England contributed to the spread of Covid-19.[11] We exploit the fact that until the Football authorities stopped outdoor sports in mid-

[10] We would like to thank Gary Ekins from https://www.footballwebpages.co.uk/ and Peter Ormosi for their help in constructing the datasets used in this paper, and Steven Bosworth, Stephen Kastoryano and Carl Singleton, along with seminar participants at Aston University, the University of Bologna and the University of Reading for their comments on an earlier version of this paper. All errors remain our own.

[11] For the avoidance of doubt, when we refer to football in the remainder of this thesis we refer to association football, soccer, or European football, as opposed to American football.

March, attendance at football matches across England carried on despite Covid-19 starting to spread rapidly[12].

The demand for attendance at sports is a richly studied phenomena (see, for example, Soebbing for Major League Baseball in the US (Soebbing, 2008), Coates and Humphreys for American football (Coates and Humphreys, 2010), Coates and Humphreys for ice hockey in North America (Coates and Humphreys, 2012), Forest and Simmons for English football (Forrest and Simmons, 2006, Forrest and Simmons, 2002a), Garcia and Rodriguez for Spanish football (García and Rodríguez, 2002), Owen and Weatherston for rugby union in Australia (Owen and Weatherston, 2004), and Paton and for Cooke cricket in England (Paton and Cooke, 2005). A common determinant of attendance is believed to be the level of uncertainty surrounding the match outcome. Furthermore, for football a number of papers have examined attendance in specific settings, for example Peel and Thomas look at repeat league fixtures between the same Scottish clubs (Peel and Thomas, 1996), whilst Szymanski compares matches between the same clubs across different competitions in English football (Szymanski, 2001). Wallrafen consider lower division football in Germany (Wallrafen et al., 2019), and Chabros look at non-league football in England, paying particular attention to the rules prohibiting the live broadcasting of matches on a Saturday afternoon (Chabros, 2019).

These studies of determinants of attendance have not considered the risks associated with the consumption of a good. In contrast, outside of sport, Becker and Rubenstein consider the impact of a terrorist attack on the demand for public transport in Israel (Becker, 2011); they find that only demand from occasional users was affected. Turning to health-related risks, Kuo et al (Kuo et al., 2008, Kuo et al., 2009), Lean

[12] https://www.thefa.com/news/2020/mar/13/fa-premier-league-efl-statement-football-suspended-130320#:~:text=The%20FA%2C%20Premier%20League%2C%20EFL,3%20April%20at%20the%20earliest. (Accessed 12/9/24) Although the Government later announced a full national ‘lockdown’ preventing fans from attending matches, the football authorities acted earlier on 13 March 2020 to stop matches from being played.

and Smith (Lean and Smyth, 2009), and Mao et al (Mao et al., 2010) find that Avian Flu and SARS had a significant, but relatively short-term effect, on tourism demand in South-East Asia. Similarly, Rassy and Smith (Rassy and Smith, 2013) finds that the 2009 H1N1 pandemic in Mexico had significant short-term effects on the tourism and pork sectors. In terms of impact on sport, Gitter shows that the H1N1 pandemic resulted in a fall in attendance at Mexican baseball of 15-30% (Gitter, 2017). Reade and Singleton, look at the impact of the Covid-19 pandemic as it spread throughout Western Europe on attendance in the top football leagues, finding mixed effects (Reade and Singleton, 2020). Finally Reade et al, consider attendances at games in the Belarusian league which was the one professional football league in Europe that did not suspend the season during the Covid-19 pandemic (Reade et al., 2020). They find that after an initial fall, attendances recovered, thus suggesting that fans were not self-distancing spontaneously.

In contrast, a smaller number of papers have considered the impact of attendance at mass events on the spread of a virus. Stoeker, et al. find that a US city having a team in the Superbowl saw an 18% increase in influenza deaths amongst the over-65 population in that city (Stoecker et al., 2016). In contrast, they find that there is no effect on the city hosting the Super Bowl. They argue that the effect on the finalist's city can be attributed to transmission via parties and bar visits to watch the club in the final and qualification games. Cardazzi, et al. look at the long term impact a sport club franchise has on the spread of influenza in US cities over many decades (Cardazzi et al., 2020). They find that hosting a franchise, results in between 4% and 24% more influenza deaths in the years proceeding. The only study so far to consider explicitly the impact of mass events on the spread of Covid-19 in the US is Ahammer et al, who look at indoor basketball and ice hockey events in the US (Ahammer et al., 2020). They find that these events led to around 380 more Covid-19 cases and 16 more deaths per one million people in the counties the events took place in. Our study differs to this previous literature by examining how mass outdoor events outside the US contributed to the spread of virus. Thus, it provides evidence on how mass outdoor events can spread Covid-19. Our findings are particularly important from a public policy perspective, as football represents a significant mass outdoor pastime across much of Europe and indeed the world, and patterns associated with attendance at football matches differ significantly from attendance at North American sports. In particular, in Europe it is much more common for fans to travel to watch their club playing away from home.

Football in England provides us with a rich setting to examine the spread of the virus. Every season, millions of fans across the country attend football matches in their local area. In stadiums fans are often packed tightly together and also congregate together both outside and inside the stadia. It is also important to note that a significant proportion of the fans attending a game are visiting spectators who travel to watch their club play at their opposition's stadium. These fans are usually sectioned off in a separate part of the ground, but often travel on the same trains or buses and access the same bars and restaurants as home fans. Despite being outdoor events where the spread of a virus is less likely, taken together, all these factors suggest that there is great potential for English football matches to be `super spreaders', where a virus like Covid-19 can spread from person to person (Hamner, 2020).

To examine this further, we compiled a database of football matches from the 2019/20 season, covering the top eight tiers of football leagues (from the Premier League all the way down to seven sub-regional leagues that constitute the eighth tier – this is a different dataset to that which we use in Chapters Two and Three which exclusively focuses on the non-league structure). We also collected data on Covid-19 cases, deaths and excess death rates by local authority area and a range of demographic indicators. Until the government stopped outdoor sports in mid-March, attendance at football matches across England carried on despite Covid-19 cases and deaths increasing. These events were spread around the country; 247 of the 313 geographic areas we consider regularly have football being played in them and 93 of these have more than one football club across the top eight levels of English football. Furthermore, the nature of the fixture calendar means that there was random variation across these areas in the number of matches taking place in March as Covid was spreading. This allowed us to analyse whether different levels of fans attending matches across these local areas had a lagged effect on the Covid case or death rate. In addition, given that many fans travel across the country to see their club play away from home, we estimate the effect on cases and deaths in the local area of the away club as well as the home club.

We consider specifically football matches in England in March 2020, shortly before football was suspended, and we evaluate their impact on Covid-19 cases, deaths and excess deaths in April 2020. We find that there were significant positive effects of matches on cases and deaths before we added the demographic control variables such as population density, age, and ethnicity. Furthermore, adding the controls reduced the magnitude of these effects, but they remained significant for deaths and excess deaths. The results suggest that an additional match taking place in an area in March increased Covid-19 deaths by 2-3 per 100,000 people in that area.

Our results also suggest that attendance at matches can have this effect even when the stadia in which the matches take place are far from full. Furthermore, we also show that matches not only impact on the spread of the virus in the area in which the match took place, but also the area from which the away club's supporters have travelled from. Overall, our results suggest caution in returning to unrestricted spectator attendance at matches.

1.2 Data

Our dataset comes from a range of sources. We collect data on Covid-19 cases and deaths from the Office for National Statistics.[13] Figures 1-3 plot these series, and document the extent to which Covid-19 spread across England in March and April 2020. We identify 313 distinct geographic areas of England.[14]

In Figure 1 the cumulative numbers of cases in each area of England are plotted for March and April. There is considerable variation across areas, with many having well below 100 cases per 100,000 people at the end of April, a mass of areas with up to 400 cases per 100,000, and one area, Barrow-in-Furness, recording around 800 cases per 100,000.

In Figures 2 and 3, the distribution of Covid-19 deaths and excess deaths per 100,000 people is plotted for March in black and April in red. For Covid-19 (Figure 2), the distribution is tightly centred between 5 and 10 deaths per 100,000 people in March, and there is much more variance in April where it is centred around 40 deaths per 100,000 people.[15] For excess deaths (Figure 3), the difference in distributions is not as stark, but it moves significantly to the right into April where it is centred around 130 deaths per 100,000 people.

[13] https://www.ons.gov.uk (accessed 11/2/2024)

[14] These areas are local authority council areas and are the smallest areas that can be consistently defined across the country and for which disaggregated demographic information is available. They are centred around population masses and the average area has a population of almost 170,000.

[15] I.e. the additional number of deaths relative to the same month over the previous five years.

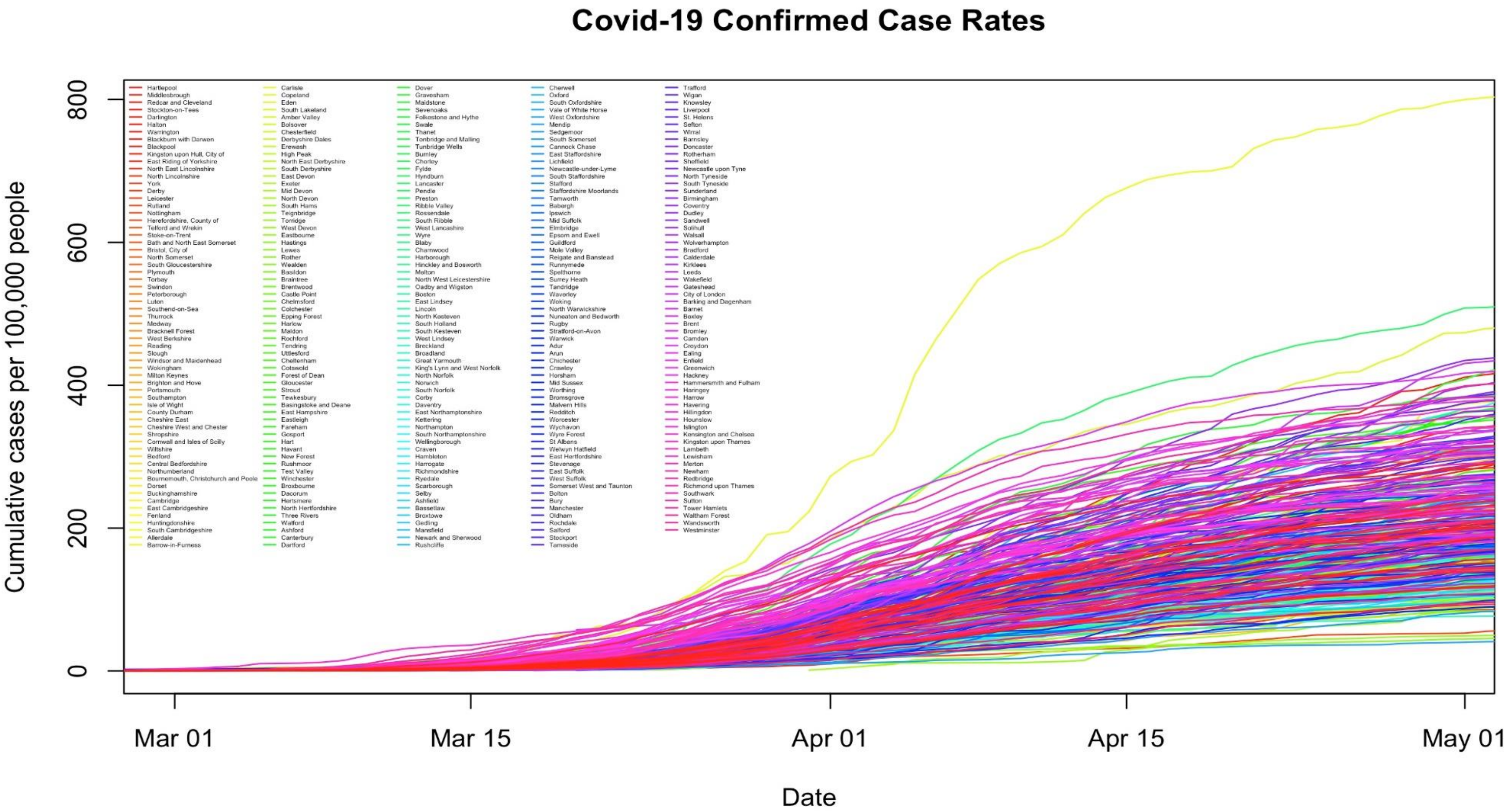

Figure 1. Covid-19 Confirmed Case Rates

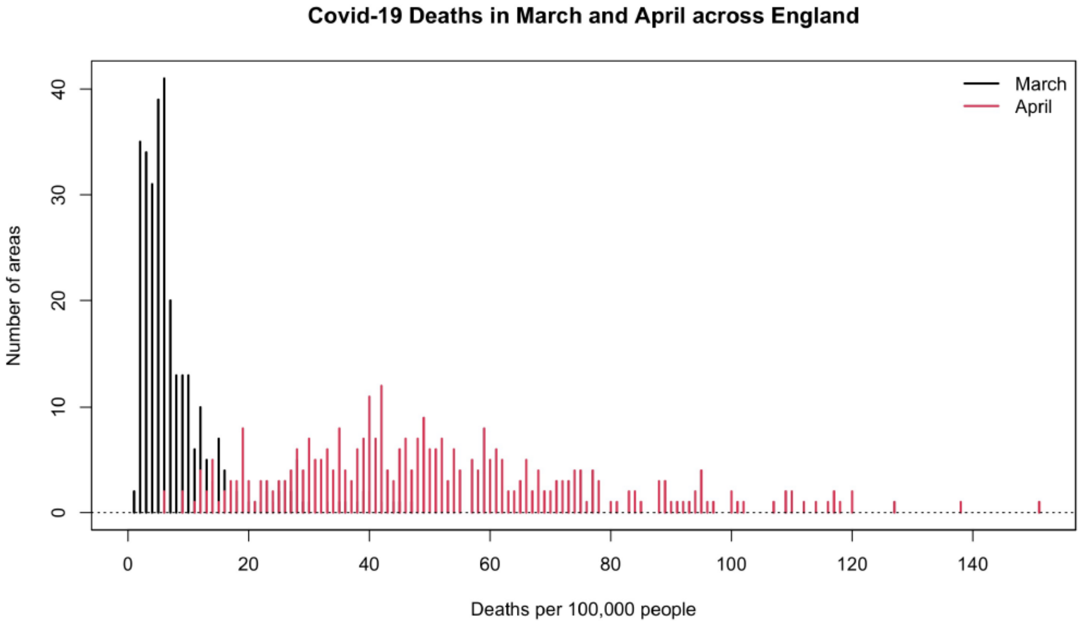

Figure 2: Distribution of Covid-19 deaths per 100,000 people in all areas across England.

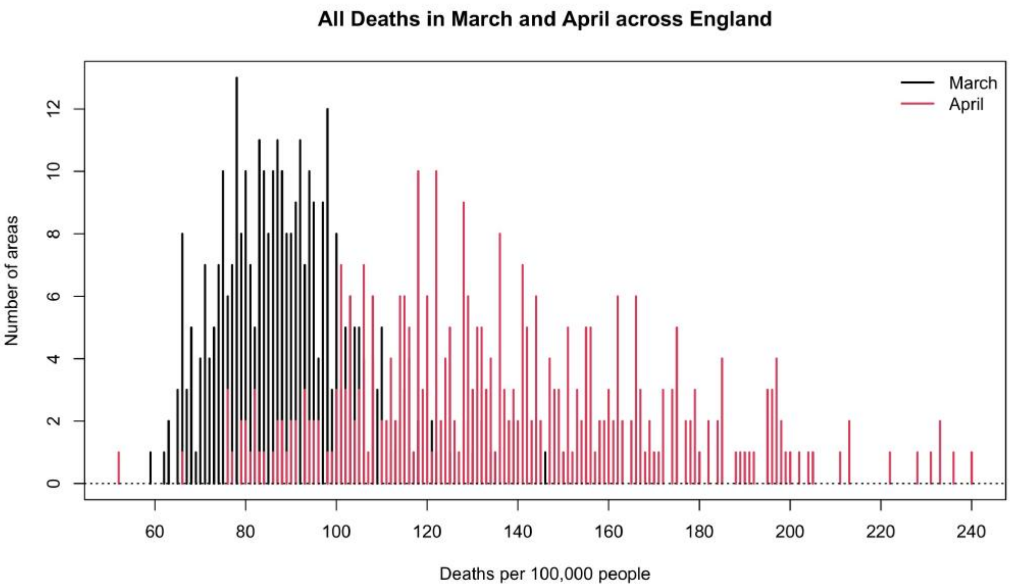

Figure 3: Distribution of excess deaths per 100,000 people in all areas across England.

Our football data are matches in the 2019--2020 season of English football from www.footballwebpages.co.uk. We include all of the top eight levels of the English football league system with data. Thus the matches cover the English Premier League (288 matches), the top division in England, all the way down to seven sub-regional leagues that constitute the eighth tier, via the EFL (tiers 2 to 4, 1284 matches), the National League (tier 5, 452 matches), National League North and South (tier 6, 733 matches), four regional leagues covering the North, Midlands, South and East of England (tier 7, 1392 matches), and the seven sub-regional leagues below them (tier 8, 1956 matches). In addition, we include matches in the two major knock-out English cup competitions (the FA Cup and the League Cup).[16]

Finally, we also include matches from the two European competitions that English clubs competed in (the Champions League and the Europa League), collected from https://www.worldfootball.net/.[17] Football in the top four tiers was suspended on March 13, with the remainder of the lower leagues the following week. As such, the final matches in our sample take place on March 14. Table 1.1. provides further information on when the matches in our sample took place. Importantly, note that 909 matches took place in February and 340 in March. Therefore, fans were still attending matches as the number of Covid cases and deaths started to grow rapidly. Furthermore, the matches in our sample took place across most parts of England. Of the 313 geographic areas of England that we consider, 247 had a club present. Ninety-three of these have more than one football club across the top eight levels of English football.

Table 1.2. shows that in the 2019--2020 season up until the suspension due to Covid-19, the average attendance in England's top tier was 39,410 and in the second tier it was almost 20,000. As low down as the sixth tier, average attendances were still around 1,000 people. For all of the matches in our sample we added information on the capacities of the stadia collected from www.footballgroundmap.com.

[16] These matches consist of 888 FA Cup matches that took place before the Covid-19 suspension, with 56 taking place in January, six in February and eight in March 2020 and 121 League Cup matches, of which four took place in January (2 two-match semi-finals), and one in March, the final at Wembley Stadium in London.
[17] There were 15 Champions League, and 14 Europa League matches, of which four were in late February and one was in March.

Figure 4 then plots the distribution of the percentage of stadia filled at matches during the season. The bulk of matches are played in stadia less than 20% full, but there is also a concentration of matches with capacity above 90%, coinciding generally with Premier League matches where on average 96.7% of a stadium's capacity was filled (Table 1.2.). Given the geographic dispersion of clubs, it follows that 39 of the areas we consider have regular matches with stadia more than 80% full.[18]

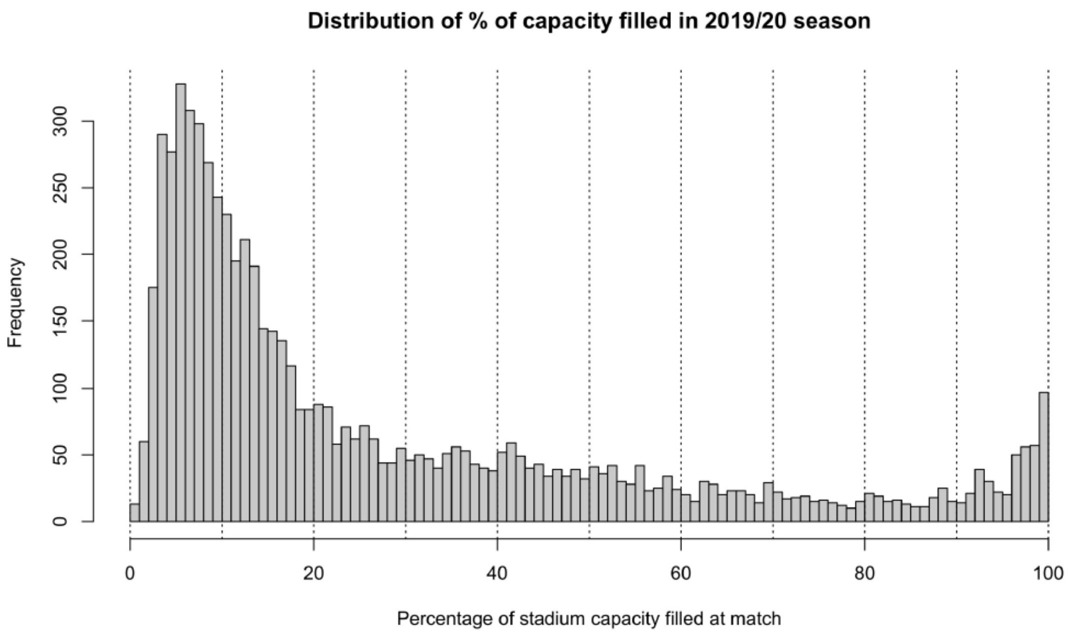

Figure 4: The distribution of the percentage of a stadium full in matches during the 2019–2020 season in all competitions covered in our dataset (6,612 matches).

For the top tier games, it is clear that fans are typically packed tightly together in the stadium. However, whilst for lower tiers capacity utilisation falls (e.g. down to 45% by the fourth tier), upon arrival fans will often be filtered in and out of the stadium through the same turnstiles and usually congregate in groups, often for the purpose of singing and shouting in support of their club. These are activities known to assist in

[18] Of the 419 matches with capacity at or above 90\%, 264 are in the Premier League, 82 are in the Championship, and 57 are in cup competitions.

the spreading of an airborne transmissible virus (Wang et al., 2021), although at the time the matches took place the vast majority of people were unaware of this. Fans also congregate in pubs and bars before and after matches and in the stadia on concourses behind stands to consume refreshments and visit bathrooms. As such, even sparsely attended stadia may provide an environment in which a virus can easily spread. Another key characteristic of these football matches is the sizeable presence of ‘away’ fans (around 10% of the fans attending a game) who travel, often significant distances, to watch their club play at their opposition's stadium. These fans are usually sectioned off in a separate part of the ground, but often travel on the same public transport and access the same pubs and bars as home fans. Consequently, an important part of our analysis will be to consider whether capacity utilisation in stadia affects the spread of Covid-19. Also, whether a match taking place affects the spread of the virus in the area the away fans have travelled from as well as the area the match takes place in.

Table 1.1. Breakdown of matches by competition/tier

	Aug 2019	Sep 2019	Oct 2019	Nov 2019	Dec 2019	Jan 2020	Feb 2020	Mar 2020
Champions League	0	1	5	5	1	0	2	1
Europa League	2	2	2	3	2	0	3	0
FA Cup	389	263	87	62	17	56	6	8
League Cup	84	17	8	0	4	4	0	4
Premier League	38	32	30	36	63	41	36	12
Championship	72	36	59	59	73	51	81	13
League One	64	51	50	34	56	56	72	17
League Two	72	60	56	35	58	72	71	16
National League	96	70	57	57	47	51	47	27
NL North and South	174	87	51	79	91	110	96	45
Tier 7	239	137	181	169	151	239	201	75
Tier 8	279	223	170	284	237	347	294	122
Total	1509	979	756	823	800	1027	909	340

Table 1.2. Stadium Attendance figures for English Football in the 2019-2020 season.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Premier League (tier 1)							
Attendance	280	39,410	16,187	10,020	27,110	53,480	73,737
Proportion of capacity filled	280	0.967	0.038	0.808	0.956	0.993	1.024
Championship (tier 2)							
Attendance	435	18,592	6,368	8,965	13,011	22,611	36,514
Proportion of capacity filled	435	0.716	0.169	0.357	0.589	0.853	1.002
League One (tier 3)							
Attendance	388	8,790	6,403	1,816	4,882	9,436	33,821
Proportion of capacity filled	388	0.542	0.179	0.156	0.436	0.649	1.014
League Two (tier 4)							
Attendance	434	4,680	2,774	1,389	3,028	5,129	17,668
Proportion of capacity filled	434	0.451	0.144	0.155	0.347	0.547	0.928
National League (tier 5)							
Attendance	446	2,187	1,278	407	1,250	2,911	9,090
Proportion of capacity filled	446	0.316	0.138	0.090	0.218	0.384	1.053
National League North (tier 6)							
Attendance	360	1,076	680	160	574	1,356	4,019
Proportion of capacity filled	360	0.227	0.130	0.040	0.135	0.313	0.753
National League South (tier 6)							
Attendance	349	867	531	185	481	1,042	3,132
Proportion of capacity filled	349	0.247	0.165	0.074	0.131	0.304	1.044

1.3. Methodology

To examine whether attendance at football matches spread the Covid-19 virus, we estimate a number of models of the form:

$$y_{it} = \alpha_i + \beta football_{it} - 1 +_y X_i + \epsilon i \qquad (1)$$

where a measure of the spread of the virus in area *i* by time *t*, y_{it}, is a function of football taking place in area *i* during time period t - 1, a set of other variables *Xi* capturing the demographics of area *i* and an error term, ϵi.

Although there is a time element to (1), we estimate a series of cross section regressions. We consider the spread of the virus by a particular point in time, *t*, and examine the extent to which they are explained by standard controls and by the presence of football matches in a preceding time period. The test of the hypothesis that football matches acted to spread the virus is then whether β>0.

It is understood that the length of time from transmission of Covid-19 to it presenting itself is around two weeks (Lauer et al., 2020). Furthermore, Covid-19 can remain symptomless in many people (Bai et al., 2020) and as such, if somebody caught Covid-19 at a football match in February or early March, it is possible they may have passed the virus to others whilst unaware, and the spread of the virus could be significantly larger as a result of the football match. Subsequently, cases may become more severe and result in a death. As such, we consider the impact of matches taking place in February on the spread of the virus in March and matches in March on its spread in April.

We consider three measures of the spread of the virus, yit

1. The cumulative number of Covid-19 cases in the area per 100,000 people *(Cases)*
2. The number of Covid-19 deaths in the area in a month per 100,000 people *(Deaths)*
3. The excess death rate in the area in a month per 100,000 people *(Excessdeaths)*

The inclusion of excess deaths is important since the Covid-19 testing procedure may be imperfect and indeed many people were not tested.

For *footballit-1* we then consider a range of measures of football taking place in an area during time period *t-1.* Our first measure, Number of matches (*No*), is a count of the total number of matches taking place in the area during the time period, *Nit* - 1. Second, if we denote the attendance at match *j* taking place in area *i* during time period *t-1* as *Ajit-1.* We then include the Total attendance at matches (Att) which is the sum of attendances across all matches in an area in a time period:

$$\sum_{j=1}^{Nit-1} Ajit - 1 \qquad (2)$$

Finally, we also consider the capacity utilisation in each match. Denote *Cjit-1* as the stadium capacity for match *j* in area *i* during time period *t-1.* We then create a series of indicator variables, D*jit*-1 where D*jit*-1=1 if A*jit*-1/ C*jit*-1 ≥ *k*, where 0< *k* ≤1, and 0 otherwise. Thus, D*jit*-1=1 if the match had capacity utilisation equal or greater than some threshold *k*. We then include the count of the number of matches in area *i* during time period *t-1* with capacity utilisation of *k* or above:

$$\sum_{j=1}^{Nit-1} Djit - 1 \qquad (3)$$

and the count of the number of matches with capacity utilisation below the threshold *k*:

$$Nit - 1 = \sum_{j=1}^{Nit-1} Djit - 1 \qquad (4)$$

Finally, because the measures in (2) and (3) give a discrete representation of capacity utilisation across football matches in an area, we also consider:

$$\frac{1}{Nit-1} \sum_{j=1}^{Nit-1} \left(\frac{Ajit-1}{Cjit-1}\right)^2 \equiv Sit - 1 \qquad (5)$$

This provides a continuous measure of capacity (Cap) that weighs more heavily the matches that were close to capacity and is bounded between 0 and 1.

Our controls included in *Xi* consist of the population density, the median age, the proportions of the local population between 16 and 64, the proportion of an area that is categorised as being of an ethnic minority, the average income level of an area, and the number of Premier League and EFL clubs (i.e. top four tier) in an area.[19]

[19] All demographic variables are from the Office for National Statistics

Table 1.3. Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Cumulative lab confirmed cases rate March 14 (per 100,000 people)	313	2.292	4.257	0	0	3	35
Cumulative lab confirmed cases rate April 30 (per 100,000 people)	313	188.388	108.122	0.000	126.300	247.900	795.400
March Covid-19 death rate (per 100,000 people)	313	8.018	8.937	0.000	2.800	9.500	47.100
April Covid-19 death rate (per 100,000 people)	313	51.840	26.600	0.000	32.900	66.600	150.700
March excess death rate (per 100,000 people)	313	90.486	16.199	59.200	78.500	99.700	146.300
April excess death rate (per 100,000 people)	313	138.280	35.299	51.900	113.600	161.700	239.900
Population (000s)	313	168.028	114.323	7.375	97.277	206.125	1,073.045
Population Density (people per square km)	313	1,816.553	2,664.425	25	229	2,423	16,427
Median Age	313	42.230	5.099	29	38	46	54
Working age 16–64	313	61.524	3.730	53	59	63	75
Proportion White English/Welsh/Scottish/Northern Irish	313	83.962	16.604	17	81	95	98
Income (GBP)	313	20,285.120	5,802.567	12,232	17,225	21,927	62,600
Number of Football Clubs	313	1.220	1.003	0	1	2	7
Number of League Football Clubs	313	0.284	0.524	0	0	1	3
Number of March matches in area	313	1.058	1.213	0	0	2	8
Number of March matches involving area	313	1.070	1.188	0	0	2	9
Number of Feb matches in area	313	2.834	2.467	0	1	4	16
Number of Feb matches involving area	313	2.818	2.607	0	1	4	22
Total attendance at March matches in area	313	4.144	13.271	0.000	0.000	1.430	116.071
Total attendance at March matches involving area	313	5.217	25.923	0.000	0.000	1.310	407.166
Number of March matches in area with 90% full stadia	313	0.061	0.276	0	0	0	2
Number of March matches involving area with 90% full stadia	313	0.073	0.398	0	0	0	5
Number of March matches in area with 80% full stadia	313	0.077	0.311	0	0	0	2
Number of March matches involving area with 80% full stadia	313	0.089	0.458	0	0	0	6
Number of March matches in area with 70% full stadia	313	0.102	0.370	0	0	0	2
Number of March matches involving area with 70% full stadia	313	0.118	0.489	0	0	0	6
Number of March matches in area with 50% full stadia	313	0.169	0.474	0	0	0	3
Number of March matches involving area with 50% full stadia	313	0.182	0.611	0	0	0	7

In Table 1.3. we present summary statistics for our data. The top panel describes the Covid cases and deaths measures (as shown in Figures 1-3), the middle panel the control variables, and the bottom panel a range of the football measures.

We consider the impact of matches taking place *in* an area on Covid-19 cases and deaths in that area. In addition, we also examine whether the spread of the virus in an area is affected when clubs from the area play away from home. We denote these as matches *involving* the area. Therefore, when Bournemouth visited Liverpool for a match on March 7th, we consider the impact of this match on the spread of the virus in Bournemouth, as well as in Liverpool. The third panel in Table 1.3. reports the number of matches involving areas, as well as matches in areas.

1.4. Results

Table 1.4. presents the impact of our first measure of football, the number of matches in an area, on Covid-19 cases and deaths in April, absent any other control variables. Normally 247 of our areas would regularly have football taking place within them. However, the essentially randomised fixture calendar and the curtailed number of fixture dates meant that in March only 187 of these areas had matches taking place within them.[20] Thus, there was random variation in the potential for matches to spread the virus across otherwise similar (especially once the controls are introduced) areas. Table 1.4. shows that the number of matches taking place in an area did have at least a weakly significant positive effect on the spread of the virus. Furthermore, this effect is more significant for excess deaths. The coefficient on total attendance is smaller because attendances are in the thousands. However, it is always highly significant, suggesting that the number of people attending these matches may have increased the spread of Covid-19.

In Table 1.6. we then report the same effects of football matches and total attendance once the controls outlined in Section 4 are added. Some of these controls are highly significant. In particular, as previously known, Covid-19 deaths were higher in lower income and less white British/Northern Irish areas. In addition, perhaps surprisingly, the spread of the virus appears lower in areas with an older population. This may be due to higher transmission of the virus in workplaces and schools in areas where a larger proportion of the population frequented these. An area's population density generally also appears to have no significant effect on the spread of the virus. Finally,

[20] The fixture calendar in football is far from random, being very purposefully put together by the various competing leagues and competitions, from domestic football to international football (at club and country level). However, for the purposes of our consideration of it, in February and March 2020 when the calendar would have been set almost a year previously, we can reasonably consider it random. Whether or not a team is at home or away, and who they play, could not reasonably be predicted, as postponements occur, and cup draws take place before each stage of the competition that a team happens to reach.

the number of league clubs in the area has no effect on the spread of the virus. Regarding, our key variables of interest, now matches and attendance have no significant effect on Covid cases. However, the number of matches now has a more significant positive effect on deaths and excess deaths. Finally, note that the total attendance at these matches is generally no longer significant once the controls are added. This suggests that it is not simply the case that the more people that attend each match, the higher the spread of the virus. We consider this further in the next section where we consider the capacity utilisation in the stadia in which the matches took place.

Table 1.4. Cases, Deaths, Excess Deaths, with number of matches (without controls)

	(1) Cases	(2) Deaths	(3) Excess deaths
Constant	179.161 * **	49.541 * **	134.045 * **
	(8.088)	(1.990)	(2.628)
Number of matches	8.726*	2.175*	4.004 * *
	(5.031)	(1.238)	(1.635)
Observations	313	313	313
R^2	0.010	0.010	0.019
Adjusted R^2	0.006	0.007	0.016
Residual Std. Error	107.775 (df = 311)	26.512 (df = 311)	35.020 (df = 311)
F Statistic	3.008* (df = 1; 311)	3.088* (df = 1; 311)	6.000 * * (df = 1; 311)

Table 1.5. Cases, Deaths, Excess Deaths, with total attendance at matches (without controls)

	(4) Cases	(5) Deaths	(6) Excess deaths
Constant	182.971 * **	49.418 * **	135.075 * **
	(6.331)	(1.509)	(2.003)
Total attendance at matches	1.307 * **	0.585 * **	0.773 * **
	(0.456)	(0.109)	(0.144)
Observations	313	313	313
R^2	0.026	0.085	0.085
Adjusted R^2	0.023	0.082	0.082
Residual Std. Error	106.892 (df = 311)	25.485 (df = 311)	33.828 (df = 311)
F Statistic	8.219 * ** (df = 1; 311)	28.907 * ** (df = 1; 311)	28.722 * ** (df = 1; 311)

Before doing so, let us summarise our key finding so far. The headline result from Tables 1.4. and 1.6. is that an additional match taking place in an area in March resulted in an additional 2 to 3 Covid-19 deaths in April per 100,000 people in that area.

1.5.1 Does capacity utilisation affect Covid-19 transmission?

Next, we analyse whether or not the transmission of Covid-19 through matches taking place in March was affected by how full the stadia were. Figure 5 gives a graphical summary of our results from running a range of variants of (1) for Covid cases and deaths.

Each point on a plot comes from a different regression equation, and each solid dot is an estimate of the β coefficient from (1) and the lines represent the associated 95% confident interval. First, to the left of the dashed line we plot the continuous capacity measure in (4) and for comparison also include the coefficients on the attendance and number of matches (as reported in Tables 1.4 and 1.6.). Then, to the right of the dashed line we look at the different thresholds (k) of capacity utilisation for each match, from 10% up to 90%. Here, the black dots represent a regression coefficient for matches with capacity utilisation equal to or *above* the threshold (2) and red dots represent matches with capacity utilisation lower than the threshold (3).

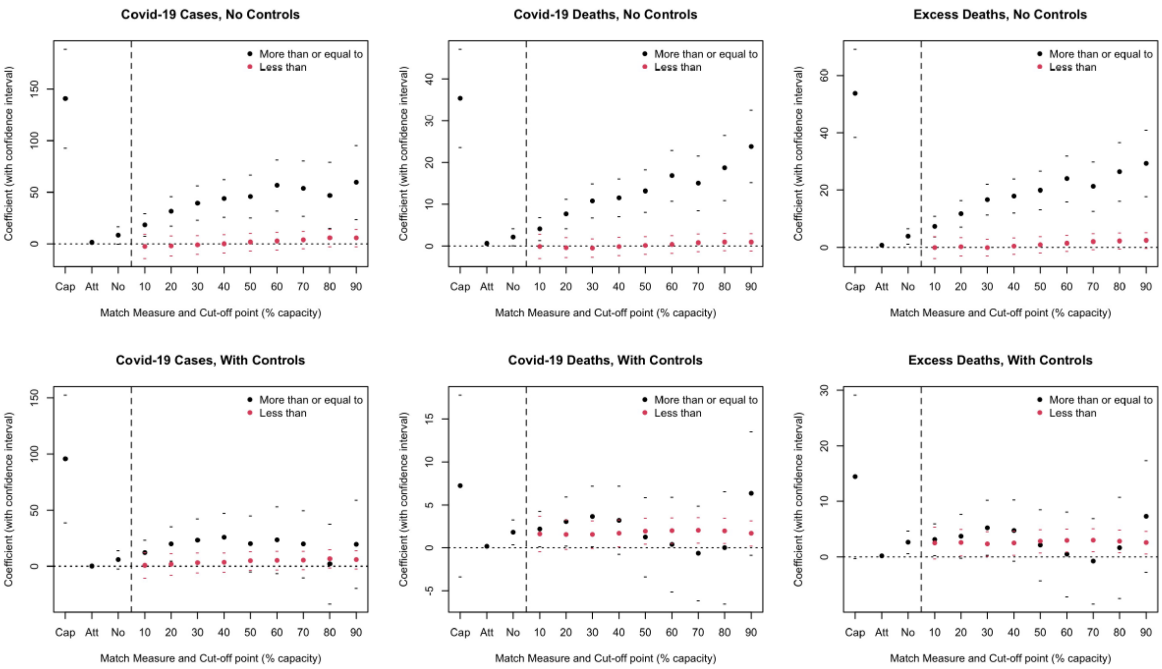

Figure 5: Summary of regression results of football match activity on the spread of the virus in the first half of 2020 in England. Each column of plots relates to one of our measures of the spread (Covid-19 cases, Covid-19 deaths, and excess deaths), the top row is without any control variables, and the bottom row adds control variables. Solid dots are regression coefficients on the footballing measure, and circles are the upper and lower confidence intervals (90% significance level).

The top row of Figure 5, without controls, suggests that matches closer to capacity are consistent with more cases and deaths in an area. The capacity measure, being bounded on the unit interval, has the largest coefficient. In addition, the counts of matches with capacity utilisation above the threshold show that each match with attendance greater than or equal to 90% of capacity is consistent with more cases and deaths than each match with attendance greater than or equal to 10% of capacity. The effect is around 50 additional cases per 100,000 people, and between 20 and 30 additional deaths per 100,000 people, for each extra match with attendance above 60% of capacity. The red dots indicate that the effect of matches below each threshold is smaller, yet close to being significant, and as such, still non-trivial.

Moving to the bottom row of plots, these are with the control variables (as in Table 1.6.) added. The notable change here is that matches below the thresholds (3) are consistently larger, relative to without controls, while the matches above thresholds (2) tend to be more varied and less distinguishable from the below ones. Because in our sample the mean capacity utilisation in a match was around 15% (Table 1.3.), the matches below thresholds have smaller confidence bands and hence, to some extent, this renders these more reliable indicators. For deaths and excess deaths, these matches are significant from less than 20-30% capacity utilisation and upwards and consistently result in between 2 and 3 additional deaths per match. For deaths and excess deaths, the effect of above threshold matches peaks in terms of significance and magnitude at 30% capacity utilisation. Matches with above 30% utilisation are consistent with between 4 and 5 additional deaths per 100,000 people, whereas this falls to 2 or 3 additional deaths for matches below 30%. Matches with capacity utilisation above this threshold also have a significant effect on the number of Covid cases and are consistent with around 25 additional cases per 100,000 people.

Overall, these results suggest that there is no straight forward relationship between capacity utilisation at matches and the spread of the virus. Certainly, the earlier effects of matches identified do not seem to be confined to matches where the stadia are close to full capacity.

1.5.2 Extensions

So far, we have considered the impact of matches taking place in an area in March on Covid cases and death rates in that area in April. Next, we first consider whether the area from which away fans travelled to the game is also affected. Second, we consider whether there is also evidence that matches in February contributed to the spread of the virus.

Tables 1.8., 1.9. and 1.10. present the effect of matches on Covid cases, deaths and excess deaths respectively, without any controls being added. For comparison, as considered earlier, the March (home) columns provide the impact in April of March matches on the area the where the match took place. Then, the March (away) results replicate this analysis but now considering the impact on cases and deaths on the area the visiting fans have travelled from. Finally, the Feb (home) and Feb (away) columns report the results for the impact of February matches on cases and deaths rates in the area the match took place and the area the visiting fans travelled from in March. Overall, these results show that the effects are generally smaller for February matches relative to March. In addition, they suggest that matches may also help to spread the virus to the area the away supporters have travelled from.
Tables 1.8., 1.9. and 1.10. present the effects of matches without controls. As before, the impact of matches on the spread of the virus tends to be significant.

Table 1.8. Effect of football matches on Covid-19 cases rates, without adding controls.

	March (home)	March (away)	Feb (home)	Feb (away)
No. matches (coef)	8.73	10.33	6.54	5.82
No. matches (p-value)	0.08	0.04	0.01	0.01
Attendance (coef)	1.31	0.34	0.78	0.64
Attendance (p-value)	0.00	0.15	0.00	0.00
Cap. measure (coef)	142.84	86.59	95.38	104.77
Cap. measure (p-value)	0.00	0.00	0.00	0.00
% of matches >=90% capacity (coef)	59.60	25.97	16.55	30.44
% of matches >=90% capacity (p-value)	0.01	0.09	0.10	0.01
% of matches <90% capacity (coef)	6.12	7.37	5.99	4.50
% of matches <90% capacity (p-value)	0.23	0.19	0.02	0.06
% of matches >=50% capacity (coef)	45.95	16.56	17.55	14.27
% of matches >=50% capacity (p-value)	0.00	0.10	0.00	0.01
% of matches <50% capacity (coef)	2.23	6.13	2.68	3.05
% of matches <50% capacity (p-value)	0.67	0.29	0.33	0.23

Table 1.9. Effect of football matches on Covid-19 death rates, without adding controls.

	March (home)	March (away)	Feb (home)	Feb (away)
No. matches (coef)	2.17	3.78	1.91	1.52
No. matches (p-value)	0.08	0.00	0.00	0.01
Attendance (coef)	0.58	0.17	0.30	0.29
Attendance (p-value)	0.00	0.00	0.00	0.00
Cap. measure (coef)	36.38	29.38	36.04	36.94
Cap. measure (p-value)	0.00	0.00	0.00	0.00
% of matches >=90% capacity (coef)	23.84	11.47	11.07	13.62
% of matches >=90% capacity (p-value)	0.00	0.00	0.00	0.00
% of matches <90% capacity (coef)	1.00	2.49	1.29	0.89
% of matches <90% capacity (p-value)	0.43	0.07	0.04	0.13
% of matches >=50% capacity (coef)	13.15	7.68	6.00	5.77
% of matches >=50% capacity (p-value)	0.00	0.00	0.00	0.00
% of matches <50% capacity (coef)	0.23	1.76	0.47	0.29
% of matches <50% capacity (p-value)	0.86	0.22	0.49	0.64

Table 1.10. Effect of football matches on Covid-19 Excess death rates, without adding controls.

	March (home)	March (away)	Feb (home)	Feb (away)
No. matches (coef)	4.00	4.96	3.00	2.67
No. matches (p-value)	0.01	0.00	0.00	0.00
Attendance (coef)	0.77	0.25	0.43	0.45
Attendance (p-value)	0.00	0.00	0.00	0.00
Cap. measure (coef)	54.84	49.77	57.79	63.96
Cap. measure (p-value)	0.00	0.00	0.00	0.00
% of matches >=90% capacity (coef)	29.34	17.62	16.11	20.66
% of matches >=90% capacity (p-value)	0.00	0.00	0.00	0.00
% of matches <90% capacity (coef)	2.59	3.11	2.13	1.72
% of matches <90% capacity (p-value)	0.12	0.09	0.01	0.03
% of matches >=50% capacity (coef)	19.92	12.10	8.80	9.56
% of matches >=50% capacity (p-value)	0.00	0.00	0.00	0.00
% of matches <50% capacity (coef)	1.09	1.81	0.95	0.65
% of matches <50% capacity (p-value)	0.52	0.34	0.29	0.43

The results in Tables 1.11-1.13. are then with the controls added. These coefficients correspond to the lower row of plots in Figure 5.

There are now few significant effects on the number of Covid cases. However, for death and excess death rates, the number of matches in both February and March has a significant positive effect on death and excess death rates in both the area the match takes place and the area the visiting fans have travelled from. Matches in March add 2-3 deaths and matches in February around one death per 100,000 people in each area.[21]

Table 1.11. Effect of football matches on Covid-19 cases rates, adding controls.

	March (home)	March (away)	Feb (home)	Feb (away)
No. matches (coef)	6.27	6.88	3.23	3.43
No. matches (p-value)	0.20	0.17	0.22	0.16
Attendance (coef)	0.18	-0.14	0.21	-0.39
Attendance (p-value)	0.74	0.59	0.49	0.28
Cap. measure (coef)	95.83	7.80	3.19	4.74
Cap. measure (p-value)	0.01	0.83	0.93	0.91
% of matches >=90% capacity (coef)	19.50	-5.53	-13.06	-4.05
% of matches >=90% capacity (p-value)	0.41	0.74	0.24	0.77
% of matches <90% capacity (coef)	6.27	7.48	4.04	3.40
% of matches <90% capacity (p-value)	0.20	0.16	0.12	0.16
% of matches >=50% capacity (coef)	20.08	-10.19	3.12	-12.28
% of matches >=50% capacity (p-value)	0.19	0.38	0.69	0.21
% of matches <50% capacity (coef)	5.28	10.01	3.10	4.03
% of matches <50% capacity (p-value)	0.30	0.07	0.25	0.10

Table 1.12. Effect of football matches on Covid-19 Death rates, without adding controls.

	March (home)	March (away)	Feb (home)	Feb (away)
No. matches (coef)	1.83	2.61	0.93	0.90
No. matches (p-value)	0.04	0.00	0.06	0.05
Attendance (coef)	0.17	-0.01	0.09	-0.00
Attendance (p-value)	0.09	0.75	0.09	0.97
Cap. measure (coef)	7.94	-1.61	-4.01	-2.33
Cap. measure (p-value)	0.23	0.81	0.55	0.76
% of matches >=90% capacity (coef)	6.33	-0.73	-0.65	1.50
% of matches >=90% capacity (p-value)	0.15	0.81	0.75	0.55
% of matches <90% capacity (coef)	1.71	2.79	0.93	0.82
% of matches <90% capacity (p-value)	0.06	0.00	0.05	0.07
% of matches >=50% capacity (coef)	1.25	-1.09	-0.20	-1.20
% of matches >=50% capacity (p-value)	0.65	0.61	0.89	0.51
% of matches <50% capacity (coef)	1.95	3.26	0.95	0.94
% of matches <50% capacity (p-value)	0.04	0.00	0.05	0.04

[21] Additional results (available on request) show that the effect is similarly significant for matches with less than 90%, and less than 50% of capacity utilisation.

Table 1.13. Effect of football matches on Covid-19 Excess death rates, adding controls.

	March (home)	March (away)	Feb (home)	Feb (away)
No. matches (coef)	2.70	2.50	1.15	1.39
No. matches (p-value)	0.03	0.05	0.09	0.03
Attendance (coef)	0.19	-0.03	0.12	0.05
Attendance (p-value)	0.17	0.61	0.14	0.62
Cap. measure (coef)	14.89	1.94	2.83	9.52
Cap. measure (p-value)	0.11	0.83	0.76	0.38
% of matches >=90% capacity (coef)	7.33	-1.46	0.65	3.48
% of matches >=90% capacity (p-value)	0.23	0.73	0.82	0.32
% of matches <90% capacity (coef)	2.65	2.75	1.11	1.21
% of matches <90% capacity (p-value)	0.03	0.04	0.10	0.05
% of matches >=50% capacity (coef)	2.14	-2.47	0.04	-0.09
% of matches >=50% capacity (p-value)	0.58	0.41	0.99	0.97
% of matches <50% capacity (coef)	2.90	3.45	1.19	1.33
% of matches <50% capacity (p-value)	0.02	0.02	0.08	0.03

Furthermore, for matches in March, the effect of a match on deaths appears to be larger on the area the visiting fans have travelled from than, on the area in which the match takes place. Overall, therefore, there is some evidence matches were contributing to the spread of the virus before March and that the effect of matches was not just confined to the area in which the match took place.

1.6 Conclusion

In this Chapter, we study the potential impact of mass outdoor events on the spread of a virus in the UK. We utilise local area level data on Covid-19 cases, deaths and excess deaths, alongside demographic variables to explain the prevalence of the virus in local areas. We then consider the extent to which football matches, of which there are usually around 200 per week across England, contributed to the spread of the virus in the first half of 2020.

We find prima facie evidence that football matches were consistent with increased cases, and deaths, during April 2020. Once we control for a range of other factors believed to help explain the spread of the virus, we find small but significant effects remain of football match activity in an area on measures of Covid deaths. We found that an additional match taking place in an area in March increased Covid-19 deaths by 2-3 per 100,000 people in that area. In addition, attendance at matches can have this effect even when the stadia in which the matches take place are far from full.

In addition, we find that the effect wasn't constrained to matches in March, with there also being evidence of some effect from matches in February. The effect of matches also was not constrained to the area in which the match took place. Instead, it appears that supporters travelling to watch their club play away from home contributed to the spread of the virus in the area they travelled from.

Overall, our analysis suggests that there should be caution in allowing fans to attend matches. This is despite the economic impact playing football behind closed doors has on clubs, particularly those outside the top tier who are far less cushioned by television income. Our findings suggest that the standard way in which fans congregate to attend matches can facilitate the spread of the virus, even if capacity utilisation in the stadium is low. Despite this, it is important to remember that the matches in our sample took place at a time when in England social distancing was not at all widespread. On the other hand, Reade and Singleton suggest that public information on the spread of Covid-19 had very little effect on fan attendance at mass events (Reade and Singleton, 2020) and Reade et al. provides evidence to suggest that fans attending football matches in Belarus did not spontaneously self-distance as the virus spread (Reade et al., 2020). However, changes in public attitudes and approaches to social distancing in the UK may still make it more feasible to allow fans back into stadiums.

Our results are consistent with the spread of the virus being exacerbated by fans congregating together both outside and inside the stadia, even when matches are sparsely attended.

Changes in fan behaviour going forward can help to alleviate these routes of transmission. Certainly, fans will need to act in a more cautious manner in future whilst attending matches. There is also scope for the layout and design of stadia to change in order to lessen the likelihood of groups of people gathering closely together (Larsson et al. consider such factors from a fire safety perspective (Larsson et al., 2021)). Government pilots to let fans back tentatively began in England but subsequently were hampered by national and local restrictions being re-introduced and it later became apparent that until there was a vaccine available, local areas and regions would continue to be shut down.[22] Further research will need to be carried out

[22] For detail on these pilot events, see https://www.gov.uk/government/news/sport-pilots-to-be-reduced-in-capacity-to-1000-people-socially-distanced

to see whether spreading fans out across stadiums, timing of entry into the stadium and changes in fan behaviour actually prevented the spread of the virus.

Fans have now been allowed to return, unrestricted, to footballing venues around the country after that range of pilot events, including the UEFA European Championships international tournament. Our results suggest that such events may still act as super spreader events, especially in the light of more transmissible variants such as the Delta variant. It will be important to re-run this analysis using the matches taking place with fans in order to examine the effectiveness of the vaccine, in particular on the tranmissibility of the virus.

Chapter 2

The impact of a 3G surface on grassroots football clubs

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2.1 Introduction

Football clubs operate in a highly competitive environment with promotion a possibility but relegation an ever-present threat. Both of these outcomes can have significant financial repercussions, meaning that decision making in this environment is crucial, in particular strategic decisions and especially those related to investments. One relatively recent development is in the playing surfaces at clubs. During the 1980's, four professional clubs in the top four leagues (now the Premier League, Championship and Leagues One and Two) had artificial pitches.[23] Whilst these are still outlawed at professional level, different levels of football were allowed to re-introduce them after 2004 if individual league structures in Europe agree locally.[24] For this chapter this is particularly relevant as Step 1 clubs voted to re-introduce them in the 2015-16 season, helping to increase the uptake of usage in English non-league football.

Amidst the wider community benefits of such investments, such as increased usage by more teams with reduced maintenance, it is possible there is a measurable impact on widely reported metrics on the playing side for clubs. In this Chapter we investigate precisely this, considering whether there is an impact of a 3G surface on match day attendances, and on match outcomes. It is important for clubs and the league competitions they belong to in understanding these potential spillover effects of investments as they consider whether to encourage such investments or not.

We consider the factors that affect demand for attendance at football matches and the effect on home and away club on-pitch performance, where the home club has an

[23] https://www.bbc.co.uk/sport/football/29894478 (accessed 12/9/24) these teams were Queens Park Rangers, Oldham, Luton Town and Preston North End.
[24] https://web.archive.org/web/20070101191110/http://www.uefa.com/uefa/Keytopics/kind=1048576/newsId=256667.html (accessed 12/9/24) UEFA allows artificial pitches again in 2004.

artificial grass (3G) pitch installed. We aim, in this Chapter, by examining the use of 3G pitches, to address the gap in the literature, where there is very little coverage in the economics of football, of the deep layer of grassroots football that feeds into the English league structure.

To test this, we take data from 412,921 matches across the English non-league football structure between the 2011/12 to 2022/3 seasons. Financial records at this level are more difficult to come by than at the professional level, with that in mind, we use attendance at matches as a proxy for revenue. At this level of football, apart from match day income from refreshments or minor sponsorship, income is directly correlated with fans attending home matches.[25]

3G pitches in England have to be registered with the Football Association in England. These are FIFA quality pitches that are tested to BS EN 15330-1:2013 standards for Steps 1-6, below that they still have to be FA accredited. They are tested every three years[26] and are artificial turf pitches designed especially to play football on.[27]

Grass football pitches have to be treated regularly and maintained to be available for matches on a weekly basis, a 3G pitch can be far more regularly re-used without having to be re-laid or treated before the next match (they are usually guaranteed for 3 years). This gives it community value, in that it can be used across the clubs' structure and even encouraging pitch or ground sharing (reserve teams, under-18's right down to the youngest level and this then enhances the clubs profile in the community through the various individuals extended networks), importantly, although they are a significant outlay initially for a club, they then can be a significant longer-

[25] https://www.nonleaguematters.co.uk/ (accessed 20/5/2023) We would like to thank the 'Non League Matters' website where we have obtained the majority of our data from, in the form of attendance and various performance metrics.
[26] https://footballfoundation.org.uk/3g-pitch-register#:~:text=Does%20my%20pitch%20have%20to,league%20or%20competition%20imposing%20sanctions. (accessed 20/5/2023)
[27] https://footballfoundation.org.uk/3g-pitch-register (accessed 20/5/2023)

term investment and source of regularly non-match day income from external pitch-hire. Sport England estimates that a 3G pitch would cost between £1.15 million to £1.205 million depending on the size of the pitch, meaning that clubs at the non-league level would be unlikely to afford on it's own and this estimate doesn't include the lifecycle costs.[28]

Much of the literature on attendance demand in football has focused on uncertainty of outcome being hypothesised as the main driver. (Forrest and Simmons, 2002b). The home club being the favourite to win has also been a factor (Peel and Thomas, 1996). Quality of the clubs has been seen as important (García and Rodríguez, 2002) Some of these earlier theories have come slightly into question though in recent years, with studies widening across leagues such as France (Scelles et al., 2013). One of the earliest football economics papers found that geography and the quality of football (or clubs) mattered when studying attendance patterns (Hart et al., 1975). Outcome uncertainty was one factor in Portugal, but there were potentially alternate factors such as loss aversion and fans preferring their club to win at home (Martins and Cró, 2018). Serrano, et al argue that game-day demand for quality is more important than outcome uncertainty (Serrano et al., 2015).

Whilst some factors found relevant in German professional football, such as the likelihood of winning a league or being promoted remains a possibility in non-league football (Pawlowski and Anders, 2012), until a club reaches Step 1 or 2, in England, they are still very much going to be playing clubs in their own region or county, so outcome uncertainty could still be a factor in attendance. At the highest levels of sport though and football in particular, even the casual fan will have an idea of a likely winner in a given elite match, without checking bookmaker odds but they will also have an idea of whom the star players are (Buraimo and Simmons, 2015). There are

[28] https://www.sportengland.org/guidance-and-support/facilities-and-planning/design-and-cost-guidance/facility-cost-guidance

studies on less well-known and supported leagues and Reilly considers attendance demand in the League of Ireland (Reilly, 2015). Further studies on less popular leagues are available, one such study examines demand in Malaysia for competitive football, with similar reasons given again for how demand works, with competitive balance, size of league and derbies all being relevant, although greater interest in 'star players' was a factor at the time (Wilson and Sim, 1995). A study of Danish Football, found that the more extreme weather found in northern European countries had some effect on match attendance but that televised European Champions League football did not affect attendance (Nielsen et al., 2019).

In other factors to consider, seasonal home advantage in English professional football is more about locality than having to travel as away club or crowd support, the effects of crowd support are not the most important (Peeters and van Ours, 2021). This is also important in the context of this paper, as, focusing purely on non-league games, fans actually mingle or traditionally switch ends during the match (Williams and Caulfield, 2020). At the non-league level, as one moves through the Steps it would be unlikely for a local casual fan to check odds before attending a match, nor would they necessarily have a great deal of knowledge of outcome. Buzzacchi, et al. discuss this in a paper examining equality of opportunity and outcome in sport, looking at closed leagues (with no promotion or relegation) and the open leagues such as we study in our paper (Buzzacchi et al., 2003). They find that that open leagues are less balanced, with this supporting some of our findings in the non-league football data we use, where in fact the imbalance can be greater than in professional leagues. Forest et al, suggest that home advantage can be a positive factor, especially for weaker clubs, so that the idea of having more equal quality playing squads across a league would not increase attendance as it would be more likely to entrench home advantage (Forrest et al., 2005a).

There are also anomalies where clubs with large historic followings have been relegated to more regional settings within the non-league structure and thus inflate some attendances across a division, something Pawlowski, et al, find happens in German professional football where clubs have strong away followings (Pawlowski and Anders, 2012). This is one of the factors affecting data at the top of the non-league structure, in the National League where recently relegated EFL clubs can inflate average attendances.

Pollard reviews the effect of home advantage in football and is one of the earliest to establish this as a recognised effect in competitive football (Pollard, 1986). If the home club is expected to lose then attendance may be lower (Coates and Humphreys, 2010). Importantly, Humphreys and Zhou (Humphreys and Zhou, 2015), discuss what Neale (Neale, 1964) called the 'uncertainty of outcome' hypothesis and find that it is expected home wins that are more of a driver of attendance than uncertainty and we later test for this, in this Chapter. It may even be that in some sports, uncertainty is a greater interest factor. We later in this thesis, test for whether at non-league level, uncertainty and the 'Louis-Schmeling paradox' competitive balance is overridden by the home win likelihood (Neale, 1964).

If outcome uncertainty and home advantage are only marginal factors in determining attendance at more elite level matches (Forrest et al., 2005b), then it is worth us testing for outcome uncertainty as a factor in non-league match attendance. League position, goals scored and likely promotion or relegation are likely to be strong factors to determine attendance, for the 'neutral' or less one-club aligned casual fan (Simmons, 1996). A natural experiment on the effect of fan attendances on results and match outcomes, was possible during Covid-19, where fans were not allowed to attend matches across most of Europe with away clubs being most impacted by an increase in yellow cards if fans attend (Reade et al., 2022)

There have been a few studies of the effect of artificial pitches on home advantage in England focusing on early-form artificial pitches in top-tier English Football, where an advantage was gained at home for clubs such as Luton Town & Queens Park Rangers (Barnett and Hilditch, 1993). Also more recently, in Dutch football the effect of more modern artificial pitches has been examined (van Ours, 2019) – this study found that whilst the top clubs did not have an artificial pitch, it did appear to help clubs trying to survive relegation, at the lower end of the table, if they had one and these small effects may have been sufficient to make a difference.

A case study of Maidstone United indicated that not only were all 45 of their clubs across adult and youth level clubs able to utilise the pitch but that it had other effects such as enticing better players from other clubs, due to the improved facilities (May and Parnell, 2017). However, these studies are few and the main focus has come from those studying the physical effects (mainly injuries) of playing on grass or artificial grass. Significant modern studies of the effects of these types of pitches on, on-pitch performance, are lacking (other than sports injury related) and none specifically looking at the effect outside of the professional leagues and within the field of sports economics (however loosely defined), thus indicating a potential gap in the literature.

Another area that it is commonly suggested there is an effect coming from 3G pitches, is examining the issue of sports injuries, evidence was uncovered relating to familiarity with artificial surfaces and that it aides continued performance (Granero-Gil et al., 2020). This was in a study relating to changes in direction whilst playing, where no evidence was found that different pitches alter the centrifugal force maintained by a player during a match (Granero-Gil et al., 2020) and whilst injuries are acknowledged as being a potential factor, practice can reduce this and help with performance particularly during a match.

There is also survey data, relating to preferences on artificial turf, which show the main preferences being for the evenness of the surface and that the surface is consistent – not needing to be relayed (Burillo et al., 2014), although players were less satisfied with the conditions than coaches or referees, highlighting the perception if not the reality of slight increase in likelihood of injury.

There is an ongoing discussion about whether 3G pitches cause more injuries to players or a greater quantity of different types of injuries and this matters to clubs as injuries are costly either in wages or performance. There is research to show that the impact is negligible (Ekstrand et al., 2006). It is also claimed that there is insufficient research into the exact causes of existing injuries in sport when looking specifically at surfaces (Fleming, 2011,Twomey et al., 2019). Some studies proving to be statistically insignificant when examining the differences between the two surfaces, apart from a higher rate of ankle injury in Major League Soccer (Calloway et al., 2019). A recent study of the overall literature on artificial surfaces covering 1973-2020 found that whilst some studies found no overall difference in injuries, when individual anatomical injury locations were examined there were higher rates for foot and ankle injuries on artificial turf, with knee and hip injuries being more common on newer generation turf (Gould et al., 2023), the suggestion is that the rates are similar for knee and hip injuries overall but that at the elite level these become more of a problem. There is also some evidence that ACL (anterior cruciate ligament) injuries are more common amongst women when using artificial pitches but not for males playing soccer/football (Xiao et al., 2022). In rugby, there was found to be a slightly greater risk of 'contact injuries' although, rugby when compared to football, is far more of a physical contact sport leading to players hitting the surface more regularly (Cousins et al., 2022). Sports like rugby (with less kicking than football), running, American sports like baseball, will all have different pressures on athletes (Potthast et al., 2010), and although we've found some studies purely of football related injuries the evidence from these is not particularly strong.

It would be remiss to not mention another of the controversies associated with artificial pitches, namely the potential environmental impact of replacing grass with a 3G pitch but as with the supposition around sports injuries the results are inconclusive (Cheng et al., 2014). Due to the chemical makeup of the artificial pitches, some questions have arisen around other public health risks not directly related to injuries sustained whilst playing and these are to do with the recycled rubber crumb used to make the pitches. Studies have found there is apparently no 'appreciable health risk' in terms of cases of cancer or leukaemia although studies will continue (Pronk et al., 2020) and this is why pitches have to meet FA and FIFA standards to be certified for use.

In summary, there is a consistent demand for non-league football in England, at least judging by the fact that 187,021 of our 412,921 matches have some level of attendance and that this is largely in the 1000's in Step 1 of non-league football. It is unlikely to be significantly affected, by other more high-profile matches as most non-league games take place at 3pm on a Saturday when the 3pm 'blackout' takes place (although it is possible to illegally stream matches via an overseas connection, it is not possible to legally watch for instance Premier League matches taking place at 3pm unless you attend the match in person)[29]. Clubs or matches also do not usually have 'star players' that would be sufficiently well known on a national level to draw in extra fans, especially when compared to the EFL or Premier League. There is clearly some level of competitive balance across the non-league structure although there may be some imbalance at certain points in the Step structure or at particular points in the time studied. For the most part though, leagues are competitive, they are, outside of the top league (the National League), partly geographically based and then wholly so at the

[29] https://www.bbc.co.uk/news/newsbeat-67626040 (accessed 12/9/2024) The 'Saturday 3pm Blackout' refers to the fact no matches can be shown on TV between 2.25pm and 5.25pm with the aim of encouraging fans to physically attend matches in the UK.

lowest levels. Whilst we will examine the potential benefits of 3G pitches, there are potential costs as outlined above, not least in terms of whether the pitches affect the number of injuries and have an environmental impact. These may not be measurable in our results but are of interest to clubs and policy makers in determining the overall value of these pitch types.

2.2 Data

Artificial pitches make up around 5% of available sporting facilities in England, with grass pitches making up around 47% of the total facilities. They are usually local authority owned or by schools or universities. (Sport England, 2023).

Our data consists of 412, 921 matches that take place in the seasons between 2011/12-2021/22 (we also use part of season 2023 in the total match figures and in regressions where we use all Steps and Seasons). We have attendance data for 187,021 of these matches (matches taking place at the lowest levels are usually played in front of no fans). These take place across the 7 or more steps with these steps having different numbers of leagues within each Step and some form of relegation and promotion, some of the matches we include in our regressions are from the lowest regional steps but these are only included in the 'all' section of the regressions.

We split this data on 3G pitches into three categories, firstly the data provided by the Football Foundation, detailing clubs that at that point in the season had 3G pitches, (January 2023). Secondly, we add to this data each club that had a 3G pitch at any point during the 2011-2023 period and is in our data set. In Figure 6, we can see that the 3G pitch is largely a phenomenon that has developed since 2010 and there being a particular increase in installing them from 2015 onwards which is consistent with the period we study. This increase in uptake of 3G pitches is most likely to be linked to firstly, an increase in available funding from Sport England announced in 2015. [30] And secondly and perhaps more importantly, the addition of Step 1 teams voting to re-introduce 3G pitches in the 2015-16 season.[31]

[30] https://www.thefa.com/news/2015/mar/27/premier-league-fa-and-government-outline-facility-plan-to-boost-footballs-grassroots (accessed 27/8/24)

[31] https://www.bbc.co.uk/sport/football/28589474 (accessed 12/9/24) Step 1 re-introduces 3G pitches.

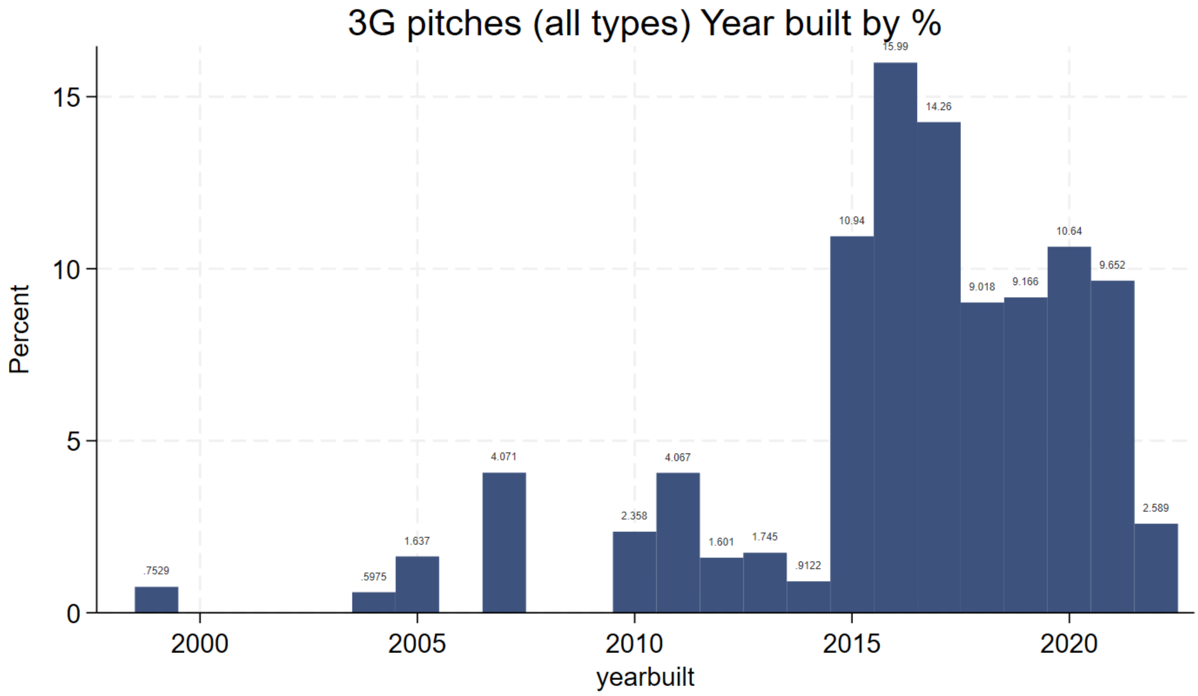

Figure 6. 3G pitches all types, with when 'built' or laid by percentage for year (data collected in 2023)

We include clubs with 3G pitches, whether they only have a 3G pitch for practice purposes and if they also use them for competitive matches, which we group together into a larger group. Finally, our third set of regressions relates to the smaller group, that is those clubs that only have the pitch for competitive match use.

The first list is of 128 clubs supplied to us by the Football Foundation of clubs with a currently in use 3G pitch for Steps 1-6. Secondly, we then supplement this by including clubs across all steps that are using a 3G playing surface purely for matches and finally all clubs with a 3G pitch, whether it be as a playing surface or for training purposes only. We hypothesize that familiarity with a pitch will potentially lead to better results, even if the pitch is not used for competitive matches, hence including those pitches used for practice only which are grouped these together with the match pitch usage to give a group which is essentially ‘any use of 3G pitch’. The first list of 128 clubs, suffers from a selection bias issue in that it only contains the clubs that were in Steps 1-6 in 2022. Thus, we expanded the list to include clubs that have a pitch for use in competitive matches and also to those clubs that have a practice pitch. We expanded the lists also to include clubs across any Step in the structure as we are covering a time period, so clubs could be promoted or relegated, this then includes them in Steps 1-6 if they are promoted. We also then are also able to include clubs relegated out of Steps 1-6 if this happens during the period studied. We include each set of results as the smaller group from the Football Foundation only, contained some interesting results, initially giving scope to the idea that 3G pitches had a significant impact, only for this to be reduced when including the wider number of clubs with pitches.

In our dataset, in total, we have 276 clubs with either a 3G playing surface, training surface or both, although this varies across the Steps. Some of these clubs are in fact, the under-23 team, reserve team or ‘development’ team that are allowed to compete in lower leagues in addition to the senior club competing at a higher level but these teams compete equally in the league structure and importantly, in this dataset are treated as separate club entities competitively. In figures 7 and 8 below, it is possible to see the slight differences in the split between the total number of clubs with either a match pitch or a practice pitch and then in figure 8 the clubs who use them for competitive matches, we’ve also demonstrated the spread by Step.

Clubs in the database range from ex-EFL clubs like Notts County who can average over 6-7000 fans per game in the National League, to clubs in regional county leagues such as East Berkshire or Cheshire at Step 7 or slightly higher where counties are often combined (Eastern Counties) or are regional (Midlands) where far fewer will attend regularly than the National League (sometimes in the hundreds but often less) and some match attendance is not recorded.

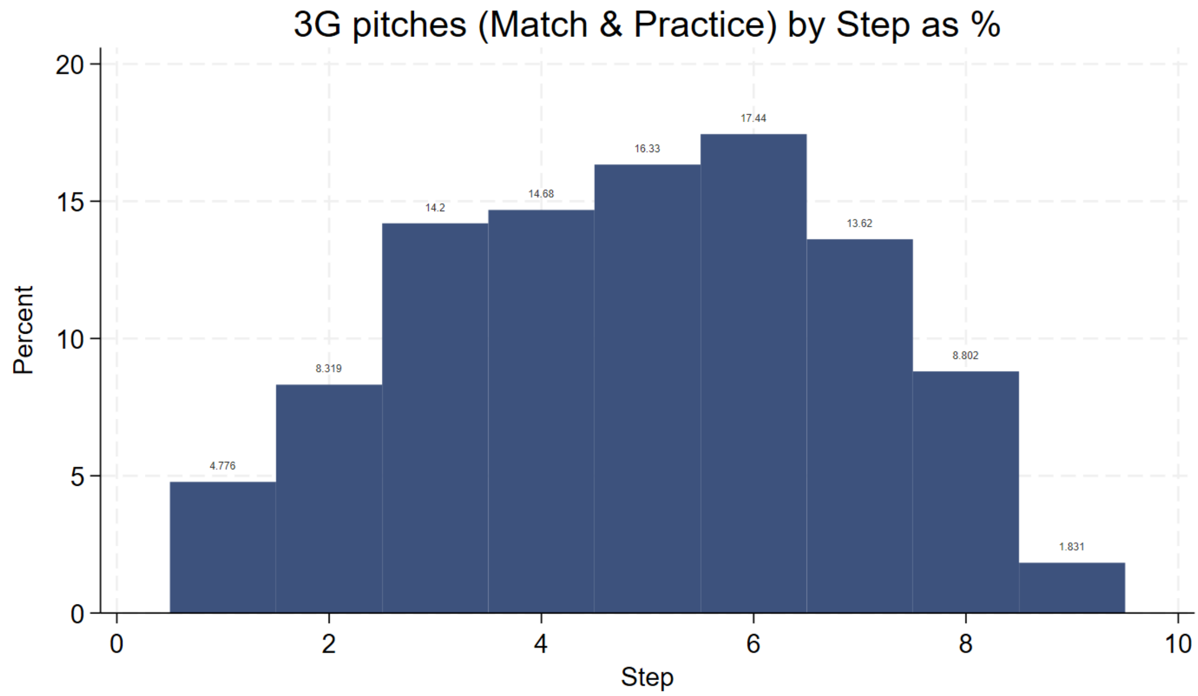

Figure 7. 3G Match & Practice Pitches by Step

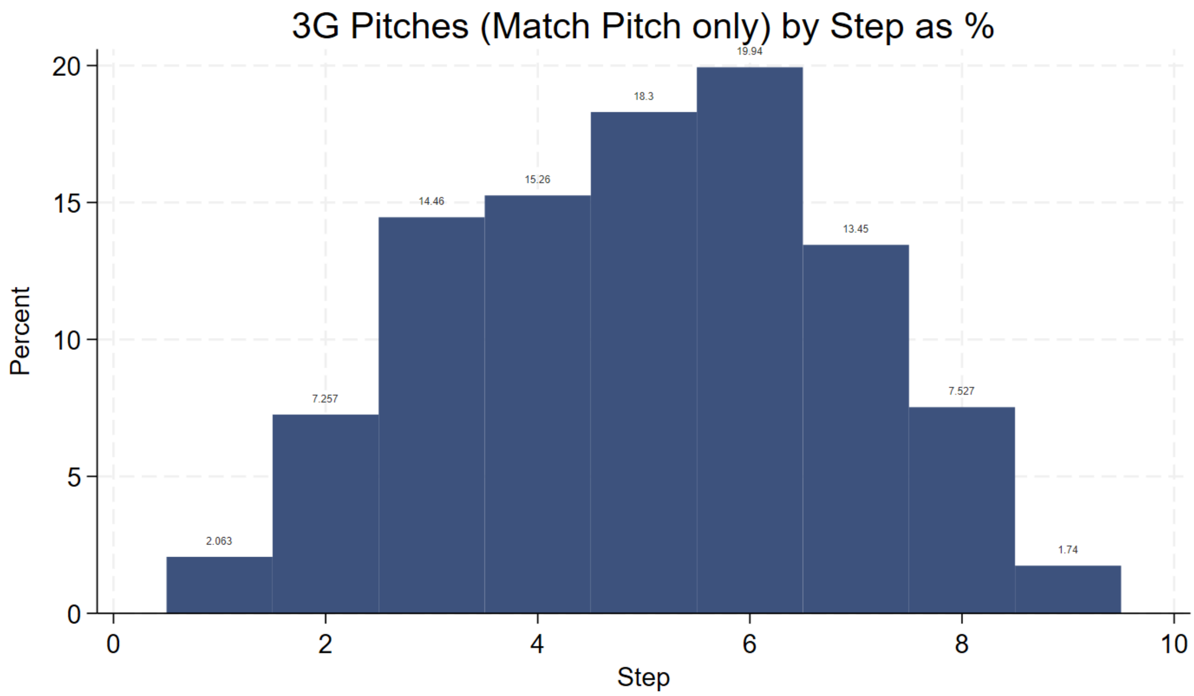

Figure 8. 3G Match pitch only by Step

Clubs are permitted to have a 3G, artificial pitch in any league across the non-league structure but not in the EFL divisions or the Premier League. If promoted from the National League and out of the non-league Step system into League Two of the EFL, then they would no longer be allowed to have that pitch due to EFL regulations (and 'ripping it up' is costly as they will not recoup the outlay costs that were made on the 3G pitch and would then have to use grass for the future, with loss of revenue from not being able to hire out the pitch any longer). There are clubs in our database that are examples of this, for instance, Sutton United & Harrogate Town and more recently Bromley. Pitches within our database have been registered with the Football Foundation and are FIFA or FA accredited according to BS EN 15330-1:2013 standards. Although we study whether 3G pitches can aide with success, there is clearly also a form of financial penalty or economic cost if the playing pitch has to be torn up if a club is promoted to the EFL.

We use a combination of the Football Foundations list of registered 3G pitches, Sport England's 'Active Places Power' database, club websites, news articles and overhead maps to confirm whether a club used the pitch for first club matches, or purely for training purposes (and also to confirm the addresses belonged to the correct club in some cases).[32] The data collected on clubs having a 3G pitch either as a first club playing surface or practice pitch is used to create binary variables indicating 1 or 0 if the clubs has one of these pitches. This data is then merged to the full 'Non-League Matters' data that covers the 2011-23 seasons. There are potential weaknesses with the data, that we do not know exactly what drives the selection of a 3G pitch. We cannot be sure for instance that better managed clubs in general are better at bidding for supporting resources and thus how much of a random selection this is. We also cannot

[32] https://dataplatform.activeplacespower.com/ (Accessed 19/9/2023)

be sure to what extent other considerations such as practical space (in the stadium area or immediate vicinity) or location of club this affect the ability to put in place this type of pitch.

It is worth noting that within the data is contained two seasons, affected by the onset of Covid-19. The first season, 2019/20 was curtailed with leagues ending abruptly in March 2020.[33] The second season started later than usual in September and even October for Steps 1 & 2 and initially fan numbers were strictly limited to up to 30% in Steps 3-6 only. The situation became more complicated as some regions of the country were restricted more than others, with different areas increasing their restrictions as time went on and additional cases of Covid increased in that area, some regions were not opened to fans attending at all. Other safety restrictions were placed on clubs, such as fans submitting to 'test and trace' regulations and not allowed to congregate within the stadium in groups larger than six.[34] Restrictions in the UK only ended fully in July 2021. This period certainly affected attendances and also a club's ability to operate financially within these restrictions as for some of the clubs in Step 1 & 2 they would regularly achieve well over 50% of capacity at home games and a forced reduction would obviously affect profits. This is within a closely managed financial system where clubs would already have lost revenue due to earlier forced match closures.

[33] https://www.thefa.com/news/2020/mar/19/joint-fa-efl-premier-league-statement-update-on-professional-football-covid-19-190320 (Accessed 01/02/2024). Football Association statement on continuing postponement of EFL matches. Whilst professional football resume to complete it's games in May, June and July, the National League games were cancelled and league's stopped: https://www.thenationalleague.org.uk/national-league-statement-remaining-league-matches-61884 (Accessed 01/02/2024)

[34] https://www.thefa.com/news/2020/aug/19/updated-guidelines-for-return-of-spectators-190820 (Accessed 23/10/2023)

We present summary statistics initially in two forms, firstly the main variables used across the different regressions (Table 2.1.). Secondly this is shown by each Step (Table 2.2.), with the number of matches taking place with each type of 3G pitch and including attendance, log attendance and goals.

Table 2.1. Summary statistics, all Steps,

Variable	Obs	Mean	Std.Dev	Min	Max
3G Match and Training Pitch	414,086	0.053	0.224	0	1
3G Match pitch only	414,086	0.037	0.190	0	1
Home Goals	414,086	2.124	1.878	0	28
Away Goals	414,086	1.837	1.687	0	30
Season	414,086	2015.971	3.299	2011	2022
Outcome Home Win	414,086	0.453	0.498	0	1
Outcome Draw	414,086	0.173	0.378	0	1
Outcome Away Win	414,086	0.374	0.484	0	1
Elo prediction	414,086	0.500	0.125	0.048	0.952
Home Points (when match takes place)	414,086	21.207	17.625	0	119
Away Points (when match takes place)	414,086	21.337	17.810	0	113
Home Wins	414,086	6.201	5.396	0	39
Away Wins	414,086	6.245	5.458	0	37
Matches Played	414,086	14.988	10.352	0	53
Total H Goals (when match takes place)	414,086	29.305	22.295	0	167
Total A Goals (when match takes place)	414,086	29.453	22.545	0	190
Home Goal Diff (when match takes place)	414,086	0.042	22.006	-279	148
Away Goal Diff (when match takes place)	414,086	0.322	22.061	-315	163
Home Lg Position (when match takes place)	414,086	9.338	5.479	1	36
Away Lg Position (when match takes place)	414,086	9.302	5.474	1	36
yearbuilt	25,104	2016.326	4.124	1999	2022
Attendance	187,492	232.995	521.348	0	16511
Log Attendance	187,148	4.693	1.071	0	9.712
Step	408,481	6.318	1.843	1	13
FF Pitch start of season	414,086	0.034	0.180	0	1
Home Goal difference per game	398,880	0.004	1.527	-18.25	18
Home goals scored per game	398,880	2.005	0.905	0	18
Saturday game	414,086	0.766	0.423	0	1
Goal difference in game (between 2 clubs)	414,086	0.287	2.749	-29	28
3G teams play each other	414,086	0.004	0.067	0	1

Table 2.2. Summary statistics for our different measures of 3G pitch classification with Log Attendance, Attendance and goals.

Step 1

Variable	Obs	Mean	Std. dev.	Min	Max
Log Attendance	5,722	7.423	0.670	5.147	9.712
Attendance	5,722	2112.344	1632.554	172	16511
Home Goals	6,145	1.489	1.279	0	9
Away Goals	6,145	1.222	1.140	0	7
Match pitch use only	6,145	0.051	0.220	0	1
Training&Matchpitch use	6,145	0.169	0.375	0	1
FootballFoundationpitches	6,145	0.062	0.242	0	1

Step 2

Variable	Obs	Mean	Std. dev.	Min	Max
Log Attendance	9,584	6.437	0.678	4.043	8.750
Attendance	9,584	796.962	649.498	57	6311
Home Goals	10,015	1.561	1.327	0	9
Away Goals	10,015	1.335	1.209	0	8
Match pitch use only	10,015	0.110	0.313	0	1
Training&Matchpitch use	10,015	0.181	0.385	0	1
FootballFoundationpitches	10,015	0.107	0.309	0	1

Step 3

Variable	Obs	Mean	Std. dev.	Min	Max
Log Attendance	17,338	5.747	0.6148	3.989	8.519
Attendance	17,338	388.120	331.5390	54	5009
Home Goals	17,358	1.648	1.3813	0	13
Away Goals	17,358	1.389	1.2671	0	10
Match pitch use only	17,358	0.126	0.3323	0	1
Training&Matchpitch use	17,358	0.178	0.3823	0	1
FootballFoundationpitches	17,358	0.133	0.3392	0	1

Step 4

Variable	Obs	Mean	Std. dev.	Min	Max
Log Attendance	29,779	5.068	0.637	2.639	8.414
Attendance	29,779	200.596	194.099	14	4512
Home Goals	29,870	1.746	1.493	0	13
Away Goals	29,870	1.517	1.348	0	12
Match pitch use only	29,870	0.078	0.267	0	1
Training&Matchpitch use	29,870	0.107	0.309	0	1
FootballFoundationpitches	29,870	0.079	0.270	0	1

Step 5

Variable	Obs	Mean	Std. dev.	Min	Max
Log Attendance	56,355	4.437	0.683	0.693	8.460
Attendance	56,370	110.893	134.787	0	4720
Home Goals	59,855	1.910	1.640	0	15
Away Goals	59,855	1.678	1.492	0	15
Match pitch use only	59,855	0.046	0.210	0	1
Training&Matchpitch use	59,855	0.059	0.236	0	1
FootballFoundationpitches	59,855	0.043	0.204	0	1

Step 6

Variable	Obs	Mean	Std. dev.	Min	Max
Log Attendance	54,634	4.064	0.653	0	7.781
Attendance	54,658	74.118	79.444	0	2395
Home Goals	63,142	2.072	1.803	0	18
Away Goals	63,142	1.796	1.617	0	18
Match pitch use only	63,142	0.048	0.214	0	1
Training&Matchpitch use	63,142	0.060	0.238	0	1
FootballFoundationpitches	63,142	0.049	0.215	0	1

Step 7

Variable	Obs	Mean	Std. dev.	Min	Max
Log Attendance	10,122	3.715	0.596	0	6.409
Attendance	10,270	48.327	34.016	0	607
Home Goals	105,626	2.223	1.940	0	25
Away Goals	105,626	1.926	1.730	0	18
Match pitch use only	105,626	0.019	0.138	0	1
Training&Matchpitch use	105,626	0.028	0.165	0	1
FootballFoundationpitches	105,626	0.010	0.102	0	1

Step 8

Variable	Obs	Mean	Std. dev.	Min	Max
Log Attendance	1,473	3.387	0.579	0	5.951
Attendance	1,613	32.139	27.378	0	384
Home Goals	93,782	2.389	2.081	0	26
Away Goals	93,782	2.050	1.867	0	30
Match pitch use only	93,782	0.012	0.110	0	1
Training&Matchpitch use	93,782	0.020	0.141	0	1
FootballFoundationpitches	93,782	0.007	0.083	0	1

Step 9

Variable	Obs	Mean	Std. dev.	Min	Max
Log Attendance	5	2.678	1.548	0	3.784
Attendance	22	5.591	12.835	0	44
Home Goals	17,311	2.485	2.203	0	27
Away Goals	17,311	2.177	2.021	0	26
Match pitch use only	17,311	0.015	0.123	0	1
Training&Matchpitch use	17,311	0.023	0.150	0	1
FootballFoundationpitches	17,311	0.013	0.114	0	1

In Table 2.2. it is then clear than the Step with the largest number of games taking place is Step 7, with only 2% of those matches containing 3G pitches but as per our earlier description, this is also the step with the most leagues. We can also see the drop in attendance being recorded as less than 10% of games at this Step contain some form of attendance recorded, although that still amounts to over 10,000 matches, the games with no attendance recorded in the higher Steps are likely to refer to games in the Covid-19 period, which we refer a bit later in Tables 2.3.-2.5. In terms of percentages though, the Steps with the highest proportion of games with 3G pitches in are Steps 1-4 with the largest concentrations being in Steps 2 and 3.

In Tables 2.3-2.5. our summary statistics for each type of 3G pitch classification can be seen, this time when compared to non-3G pitches. We can that in each instance clubs with 3G pitches of any type have slightly higher average attendances across the whole dataset and that if we look at total goals scored the greatest difference is when clubs use the pitches for matches (Table 2.5.) but there is a greater difference in league position with clubs using practice pitches as well (Table 2.4.) having a slightly lower average league position (within whatever Step they are in) by nearly 0.2% less, or 0.2% average lower league position, when we exclude those clubs that only have training pitches, suggesting that if there is a difference, having a practice pitch isn't necessarily giving an average advantage in this area. We can also see the slight selection bias issue we have with the Football Foundation snapshot data from 2022 in that clubs are on average at a higher Step that clubs with our additional classifications of pitches. This means that one weakness with the data is that clubs with a 3G pitch are already slightly better than the average club without one, regardless of the classification.

Table 2.3. Summary statistics for the 3G pitch Football Foundation Football data from 2022 compared to clubs without that type of 3G pitch.

No Football Foundation 3G pitch						
Attendance	Log Attendance	Total Goals Scored (at time match takes place)	Total Goal Difference (at time match takes place)	Average League Position (at time match takes place)	Average no. of Home Goals scored per game	Goal Difference/game
227.045	4.663	29.252	-0.086	9.327	2.010	-0.003
Actual no. of goals scored in a match (home)	Actual no. of goals scored in a match (away)	Average Step	Average Goal Difference (at point match takes place)	Home Win	Away Win	Draw
2.121	1.847	6.373	0.274	0.451	0.376	0.173
Football Foundation 3G pitch in 2022						
Attendance	Log Attendance	Total Goals Scored (at time match takes place)	Total Goal Difference (at time match takes place)	Average League Position (at time match takes place)	Average no. of Home Goals scored per game	Goal Difference/game
324.757	5.165	30.813	3.747	9.638	1.882	0.202
Actual no. of goals scored in a match (home)	Actual no. of goals scored in a match (away)	Average Step	Average Goal Difference (at point match takes place)	Home Win	Away Win	Draw
2.221	1.545	4.740	0.676	0.514	0.306	0.180

Table 2.4. Summary statistics for the 3G pitch where clubs use for both practice and match use (the widest selection compared to clubs without that type of 3G pitch.

Clubs with no 3G pitch of any kind

Attendance	Log Attendance	Total Goals Scored (at time match takes place)	Total Goal Difference (at time match takes place)	Average League Position (at time match takes place)	Average no. of Home Goals scored per game	Goal Difference/game
221.125	4.644	29.107	-0.149	9.312	2.011	-0.007

Actual no. of goals scored in a match (home)	Actual no. of goals scored in a match (away)	Average Step	Average Goal Difference (at point match takes place)	Home Win	Away Win	Draw
2.126	1.851	6.397	0.275	0.451	0.376	0.172

Clubs with Training or Match use 3G pitch

Attendance	Log Attendance	Total Goals Scored (at time match takes place)	Total Goal Difference (at time match takes place)	Average League Position (at time match takes place)	Average no. of Home Goals scored per game	Goal Difference/game
360.108	5.217	32.828	3.453	9.788	1.911	0.189

Actual no. of goals scored in a match (home)	Actual no. of goals scored in a match (away)	Average Step	Average Goal Difference (at point match takes place)	Home Win	Away Win	Draw
2.089	1.587	4.913	0.502	0.484	0.328	0.187

Table 2.5. Summary statistics for the 3G pitch where clubs use for both match use (excluding those clubs that only have a practice pitch) compared to clubs without that sort of 3G pitch

All clubs with no 'match use' pitch

Attendance	Log Attendance	Total Goals Scored (at time match takes place)	Total Goal Difference (at time match takes place)	Average League Position (at time match takes place)	Average no. of Home Goals scored per game	Goal Difference/game
229.308	4.669	29.138	-0.123	9.329	2.007	-0.005

Actual no. of goals scored in a match (home)	Actual no. of goals scored in a match (away)	Average Step	Average Goal Difference (at point match takes place)	Home Win	Away Win	Draw
2.123	1.847	6.368	0.276	0.451	0.376	0.173

Match Use Pitch only

Attendance	Log Attendance	Total Goals Scored (at time match takes place)	Total Goal Difference (at time match takes place)	Average League Position (at time match takes place)	Average no. of Home Goals scored per game	Goal Difference/game
289.849	5.073	33.612	4.307	9.562	1.951	0.233

Actual no. of goals scored in a match (home)	Actual no. of goals scored in a match (away)	Average Step	Average Goal Difference (at point match takes place)	Home Win	Away Win	Draw
2.160	1.588	5.022	0.571	0.502	0.321	0.177

We also include a comparison where we show data from the 2018/19 season, with fans attending in full, pre-Covid, and data for 2020/21 which was affected by Covid restrictions and then finally, when fans were beginning to return in 2021/22 to detect whether the lack of fans or reduced attendance nullifies any home advantage from a 3G pitch, or in fact possibly enhances it. These are shown in Table 2.6.-2.7. Table 2.6. is the last full 'pre-covid' season and is also a good snapshot of a season showing various other points worth noting, not least that attendance drops considerably at Step 7, where a large proportion of matches have no fans attending. We can also see the actual highest and lowest attendance figures, with the vast differences between a club at Step 1 that for one match had just 291 fans, with the highest attendance being 8283. There are still some matches with attendances in the 1000's at both Steps 4 and 5 which shows the 'demand' for football at this level, although average attendances at these steps are between 190-110 people.

Table 2.6. 2018/19 Pre-Covid non-league matches (shown for comparison, as a 'normal' season)

Step 1

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	552	0.248	0.432	0	1
Match pitch only	552	0.123	0.329	0	1
Log Attendance	552	7.392	0.617	5.6733	9.022
Attendance	552	1977.306	1376.201	291	8283

Step 2

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	924	0.122	0.328	0	1
Match pitch only	924	0.062	0.241	0	1
Log Attendance	924	6.717	0.725	4.4543	8.7501
Attendance	924	1073.365	854.708	86	6311

Step 3

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	1,806	0.169	0.375	0	1
Match pitch only	1,806	0.132	0.338	0	1
Log Attendance	1,805	5.821	0.561	4.1271	7.8921
Attendance	1,805	399.442	275.380	62	2676

Step 4

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	2,622	0.113	0.317	0	1
Match pitch only	2,622	0.085	0.278	0	1
Log Attendance	2,619	5.110	0.583	2.6391	7.3626
Attendance	2,619	197.750	135.127	14	1576

Step 5

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	5,226	0.055	0.227	0	1
Match pitch only	5,226	0.040	0.196	0	1
Log Attendance	4,968	4.472	0.652	2.1972	7.3951
Attendance	4,968	110.478	95.160	9	1628

Step 6

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	6,301	0.071	0.257	0	1
Match pitch only	6,301	0.061	0.240	0	1
Log Attendance	5,318	4.134	0.630	1.609	6.512
Attendance	5,318	76.366	56.565	5	673

Step 7

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	9,706	0.030	0.171	0	1
Match pitch only	9,706	0.021	0.142	0	1
Log Attendance	1,388	3.751	0.604	1.099	5.940
Attendance	1,388	50.995	34.698	3	380

Step 8

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	8,637	0.018	0.131	0	1
Match pitch only	8,637	0.012	0.109	0	1
Log Attendance	288	3.308	0.573	1.099	5.951
Attendance	288	34.069	39.296	3	384

Step 9

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	920	0.064	0.245	0	1
Match pitch only	920	0.030	0.172	0	1
Log Attendance	0				
Attendance	0				

The 2019/2020 season was curtailed in March following a government lockdown and leagues were either not finished or final positions were determined based on results at that stage. The 2020/21 season though, continued with Covid still taking hold of the country, with regional lockdowns still in place or where matches did take place, the restrictions already described. What is noticeable immediately is the number of matches with attendances in the top two tiers drops drastically to around only 10% of matches taking place in front of fans. Outside of that, between Steps 3-6 matches largely took place in front of fans, where they did take place but when we compared the total number of matches in each Step, one can see the effect of games only really taking place in October to December.

Table 2.7. 2020/21 First season Post-Covid suspension of non-league competitions but with fan restrictions in place.

Step 1

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	462	0.190	0.393	0	1
Match pitch only	462	0.054	0.226	0	1
Log Attendance	47	6.802	0.482	5.820	8.342
Attendance	47	1027.596	674.874	337	4197

Step 2

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	330	0.182	0.386	0	1
Match pitch only	330	0.127	0.334	0	1
Log Attendance	26	6.117	0.581	4.575	6.983
Attendance	26	519.885	246.355	97	1078

Step 3

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	335	0.185	0.389	0	1
Match pitch only	335	0.116	0.321	0	1
Log Attendance	333	5.806	0.411	4.234	6.397
Attendance	333	359.345	135.738	69	600

Step 4

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	495	0.097	0.296	0	1
Match pitch only	495	0.075	0.263	0	1
Log Attendance	483	5.308	0.473	3.497	5.991
Attendance	483	224.362	100.042	33	400

Step 5

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	1,548	0.056	0.230	0	1
Match pitch only	1,548	0.042	0.201	0	1
Log Attendance	1,293	4.725	0.509	3.178	5.768
Attendance	1,293	128.148	66.856	24	320

Step 6

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	1,873	0.073	0.260	0	1
Match pitch only	1,873	0.058	0.233	0	1
Log Attendance	1,569	4.452	0.535	2.485	5.787
Attendance	1,569	98.685	54.734	12	326

Step 7

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	3,615	0.025	0.157	0	1
Match pitch only	3,615	0.017	0.129	0	1
Log Attendance	178	3.944	0.513	2.303	5.106
Attendance	178	58.258	28.092	10	165

Step 8

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	3,897	0.013	0.113	0	1
Match pitch only	3,897	0.005	0.070	0	1
Log Attendance	52	3.637	0.568	2.197	4.949
Attendance	52	44.827	28.999	9	141

Step 9

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	646	0.039	0.193	0	1
Match pitch only	646	0.009	0.096	0	1
Log Attendance	0				
Attendance	0				

Once government restrictions on fans attending matches were withdrawn in the Summer of 2021, this meant attendances also returned to their pre-Covid setting, with over 16,000 fans attending a Notts County match at Step 1 (see Table 2.8. below). The data for this season also gives us a very good understanding of the spread of 3G pitches across the steps and how familiar players at different levels might be with them. At Step 7 for example, there are very few 3G pitches spread across the leagues at this level, meaning that if a club does have a pitch and our results show that it gives an advantage it is more likely to show here. Likewise, the effects on pitch, may well diminish for all clubs as around a ¼ of clubs have a pitch for competitive matches at Step 2, and familiarity and advantage for clubs with any 3G pitch, is also likely to be reduced as nearly 40% have some form of pitch, whether it's for practice use or for matches. We have highlighted some issues with the data but this makes it clear that it is largely restricted to these seasons at Steps 1-6 in particular where there were no fans attending at certain points and this was largely just due to restrictions at that time.

Table 2.8. 2020/21 Post-Covid non-league, restrictions on fans attending begin to be removed

Step1

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	818	0.172	0.378	0	1
Match pitch only	818	0.046	0.211	0	1
Log Attendance	810	7.790	0.711	5.989	9.712
Attendance	810	3141.184	2464.041	399	16511

Step 2

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	1,495	0.153	0.360	0	1
Match pitch only	1,495	0.110	0.313	0	1
Log Attendance	1,368	6.780	0.602	4.963	8.414
Attendance	1,368	1054.345	677.218	143	4512

Step 3

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	2,867	0.200	0.400	0	1
Match pitch only	2,867	0.144	0.351	0	1
Log Attendance	2,857	5.964	0.615	4.007	7.892
Attendance	2,857	476.837	361.300	55	2676

Step 4

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	4,610	0.125	0.331	0	1
Match pitch only	4,610	0.099	0.299	0	1
Log Attendance	4,551	5.443	0.679	3.258	8.414
Attendance	4,551	297.903	284.056	26	4512

Step 5

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	9,294	0.074	0.261	0	1
Match pitch only	9,294	0.058	0.233	0	1
Log Attendance	8,288	4.769	0.678	2.485	8.460
Attendance	8,288	155.761	208.109	12	4720

Step 6

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	9,685	0.079	0.270	0	1
Match pitch only	9,685	0.066	0.248	0	1
Log Attendance	8,584	4.346	0.699	0.693	7.781
Attendance	8,584	102.97	127.59	2	2395

Step 7

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	16,281	0.027	0.163	0	1
Match pitch only	16,281	0.015	0.122	0	1
Log Attendance	1,574	3.894	0.580	1.386	6.295
Attendance	1,574	58.323	40.376	4	542

Step 8

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	14,031	0.013	0.112	0	1
Match pitch only	14,031	0.008	0.090	0	1
Log Attendance	544	3.498	0.554	0	5.338
Attendance	544	38.046	21.904	1	208

Step 9

Variable	Obs	Mean	Std. dev.	Min	Max
Training & match pitch	1,733	0.037	0.189	0	1
Match pitch only	1,733	0.016	0.124	0	1
Log Attendance	0				
Attendance	0				

2.3. Methodology

Our unit level of analysis is at the match level with club *i* and away club *j* at time *t*. Each regression contains a different dependent variable.

We create a range of variables using data from the Non-League Matters website, we use data at the season level and Step level as we are looking for effects at the Step level across the entire 2011-23 set of seasons.

To test our hypothesis that 3G pitches increase average attendance we use the log of attendance *LogAtt* as a proxy for the revenue of each club. We use log attendance due the wide variances in the attendance levels and differences across the dataset as seen earlier in the data section of this Chapter. Some Step 1 clubs have many thousands of fans attending, whereas in step 7 and below, matches can have as low as 5-10 people (or often 0) recorded.

We employ a standard difference in differences approach:

$$LogAtt_{Y_{ijt}} = \alpha + \beta 1_{ThreeGpitch_{ijt}} + \beta 2_{Elo_{ijt}} + \beta 2_{Elo\text{^}2_{ijt}} + \beta 3_{LgPosHome_{ijt}} + \beta 4_{LgPosAway_{ijt}} + \beta 5_{GoalsHome_{ijt}} + \beta 6_{GDHome_{ijt}} +_{\xi it} +_{eit} \quad (1)$$

The other regressions we carry out are on the dependent variables that are our on-pitch performance indicators, these are Outcome Home Win (HG), Outcome Away Win (AG), Draw (D), Home Goals (HG), Away Goals (AG) Goal Difference (GD), where Logatt is replaced by one of these options. Our main independent variable is a categorical variable indicating whether a club has a 3G pitch or not, *ThreeGpitch. A*s previously mentioned, this comes in 3 parts, the original list of 3G pitches from the Football Foundation, covering only Steps 1-6, the full list of all clubs with either a playing pitch or a training 3G pitch and finally those clubs that use the pitch for matches (shown as *ThreeGpitch*).

In each variation *ThreeGpitch* = 1 if a club has a 3G pitch.

Our control variables are a variety of firstly, the Elo prediction (*Elo*), i.e. the percentage chance either club will win based on historical results (Elo) Elo ratings are created from past results using these as a predictor when comparing the two clubs together (to show relative club strength), this then gives an estimation of the most likely result (Hvattum and Arntzen, 2010). We use home (*LGposHome*) and away league position (*LGposAway*) as these are known predictors of form over the entire season and also predictors of whether a fan may attend a match; including relative goals (goals at that point of the season) for both home (*GsH*) and away clubs (*GsA*), both are known indicators of why a fan may attend a match (Peel and Thomas, 1996) and we also include at different points, goals scored, divided by game played (*Gspg*) and goal difference divided by games played (*Gdpd*), both used again as alternate indicators of performance. We also use as controls, Goal Difference for the home club (*GDH*) at the time match takes place and Goal Scored home (*GSH*) club at the time the match takes place.

For the attendance regressions only, we utilise the version of Uncertainty of Outcome theory explored by Coates et al, and Humpherys and Zhou (Coates and Humphreys, 2012, Humphreys and Zhou, 2015,), we add in a variable that is Elo^2 to reflect demand for attendance, to see whether a predicted home win is in fact the main driver of attendance at this level of football, rather than uncertainty. As the Elo rating is a percentage of the likelihood of home win, this is squared to show when home win advantage becomes less of a factor in driving attendance. This variable also takes into account loss aversion for fans. This Elo^2 is then not used with the on-pitch performance variables as we are only interested in the effect on Log Attendance.

We also include two independent variables where clubs with a 3G pitch play each other to see if the effects are cancelled out this is shown as home club has 3G pitch for matches (*HT3G*), multiplied by away club has 3G pitch for matches (*AT3G*) leaving only the matches where both are involved.

We use fixed effects for Season, Step, Weekday and Home club and these are captured within ξijt, the home club fixed effects in particular controls for club strength and season for performance variation over seasons, with weekday controls for. Finally, *eit* is our overall error term capturing other unknown factors that may determine why a club has a 3G pitch.

We do not consider the capacity of a stadium as a factor as at this level in the data as it is only really at the professional, top two leagues in England, that clubs regularly reach capacity. We refer to this issue in Chapter One, where we discuss the effect of fans attending matches affecting the spread of Covid-19.

Whilst matches are shown as *i* the time the match takes place as *t*, each regression contains a varying number of matches (n) with observations varying across steps but also the number of clubs. When we include only matches with log attendance recorded, we lose some of the total matches due to there being no recorded attendance, we do include those matches, without attendance recorded in the other regressions where log attendance is not a dependent or independent variable.

2.4. Results

Below we present our findings from three separate tests. Firstly, we use the Football Foundation data (this is the data that includes only clubs that had 3G pitches by 2022 and were in the top 6 Steps at that time). We then examine what happens when we expand that data set across nine steps which have clubs with 3G pitches, in two forms. We include clubs in this data set that only use a 3G pitch for practice and clubs that have one for match use only. We group together the practice pitch clubs with the match pitch clubs so that all clubs with any 3G pitch are included in one set of regressions. Finally, the third set of regressions, shows those clubs that use the pitch for matches only, i.e. it excludes those clubs that have just a practice 3G pitch. This is to check that to see that experience of playing on pitches in matches rather than just practice has any different effect.

Our results in the various Tables (2.9.-2.36.) show the effect of 3G pitches on Log Attendance through to the effect on home goals, away goals, goal difference, and the match outcome – win, draw or lose. In the first set of Tables, these contain fixed effects for home club, season, weekend/weekday matches and step (Tables 2.9-2.15).[35] We then repeat these for the later data set we created which shows those clubs with 3G practice pitches and match use pitches (Tables 2.16.-2.22.) and those with match use pitches only (Tables 2.23-2.29.). Each step is shown in the top of each Table, with seven to nine steps shown (depending on available data) and the first regression on the left of the Table being all steps in the database including outside step seven.

Table 2.9. includes log attendance, which we have for 181,123 matches (although this is half the total number of matches, this is still a large enough set of data), whereas the later Tables include up to just under 400,000 matches or just over 412,000 matches. It

[35] The Tables for Outcome Draw and Outcome Away win can be found in Appendix 1. for completeness but were removed from the main thesis as they don't really tell us much more than the 'outcome home win' does for each type of regression.

also highlights why we have used log attendance, that average attendance across all matches is 232 people (which for a Step 8-9 club would be large) but the highest attendance in the whole period is 16511 people (something that the average English Championship or League One club might regularly achieve).

Table 2.9. Log Attendance for 3G pitches (original Football Foundation), with controls and fixed effects and Uncertainty of Outcome test included.

VARIABLES	(1) All Steps Log Attendance	(2) Step 1 Log Attendance	(3) Step 2 Log Attendance	(4) Step 3 Log Attendance	(5) Step 4 Log Attendance	(6) Step 5 Log Attendance	(7) Step 6 Log Attendance	(8) Step 7 Log Attendance
FF 3G Pitch for Match	0.147***	0.086*	0.092***	0.085***	0.135***	0.104***	-0.001	0.324***
	(0.007)	(0.046)	(0.019)	(0.015)	(0.014)	(0.016)	(0.022)	(0.107)
Elo Prediction	-0.310***	-2.244***	-1.225***	-1.897***	-1.095***	-0.954***	-0.420***	-0.435**
	(0.047)	(0.400)	(0.253)	(0.172)	(0.099)	(0.085)	(0.074)	(0.180)
Elo Prediction^2	0.335***	2.290***	1.075***	1.639***	0.985***	0.749***	0.261***	0.355**
	(0.046)	(0.396)	(0.252)	(0.172)	(0.098)	(0.083)	(0.073)	(0.173)
Goals Scored (Home)	-0.005***	-0.003***	-0.002***	-0.003***	-0.003***	-0.005***	-0.004***	-0.005***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Goals Scored (Away)	0.005***	0.004***	0.004***	0.005***	0.005***	0.005***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Goal Difference (Home)	0.004***	0.005***	0.005***	0.006***	0.005***	0.005***	0.005***	0.004***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
League Position (Home)	-0.005***	-0.013***	-0.011***	-0.010***	-0.009***	-0.011***	-0.009***	-0.010***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Constant	4.716***	7.962***	6.722***	6.237***	5.265***	4.780***	4.326***	4.118***
	(0.014)	(0.106)	(0.068)	(0.047)	(0.028)	(0.025)	(0.022)	(0.055)
Observations	187,148	5,722	9,584	17,338	29,779	56,355	54,634	10,122
R-squared	0.158	0.251	0.191	0.178	0.217	0.159	0.160	0.145
Number of team1id	1,566	70	104	188	325	622	757	320
Adjusted R-squared	0.151	0.240	0.181	0.168	0.208	0.149	0.148	0.116

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 2.10. Home Goals (original Football Foundation), with controls and fixed effects

VARIABLES	(1) All Steps Home Goals	(2) Step 1 Home Goals	(3) Step 2 Home Goals	(4) Step 3 Home Goals	(5) Step 4 Home Goals	(6) Step 5 Home Goals	(7) Step 6 Home Goals	(8) Step 7 Home Goals	(9) Step 8 Home Goals	(10) Step 9 Home Goals
FF 3G Pitch for Match	0.255***	0.183	0.037	0.257***	0.289***	0.447***	0.117	0.708***	3.069***	0.171
	(0.026)	(0.199)	(0.072)	(0.059)	(0.057)	(0.062)	(0.077)	(0.117)	(0.165)	(2.001)
Elopredict	1.993***	0.660**	1.157***	1.263***	1.356***	1.746***	1.939***	2.202***	2.556***	2.353***
	(0.031)	(0.257)	(0.175)	(0.134)	(0.092)	(0.074)	(0.070)	(0.065)	(0.089)	(0.250)
League Position (Home)	-0.015***	-0.007	0.004	0.001	-0.004	0.001	-0.008***	-0.010***	-0.013***	-0.016*
	(0.001)	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.009)
League Position (Away)	0.065***	0.024***	0.017***	0.027***	0.043***	0.054***	0.064***	0.089***	0.111***	0.133***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.005)
Goal Scored per game (Home)	0.134***	-0.050	0.058	0.027	0.117***	0.052***	0.087***	0.047***	0.002	-0.116***
	(0.006)	(0.064)	(0.047)	(0.035)	(0.027)	(0.018)	(0.017)	(0.013)	(0.013)	(0.034)
Goal Diff per game (Home)	0.094***	0.066	0.101***	0.093***	0.069***	0.135***	0.102***	0.107***	0.094***	0.100***
	(0.004)	(0.054)	(0.039)	(0.029)	(0.021)	(0.013)	(0.012)	(0.009)	(0.009)	(0.024)
Constant	0.280***	1.113***	0.754***	0.485***	0.331***	0.222***	0.139**	0.129**	0.060	0.405**
	(0.024)	(0.186)	(0.140)	(0.105)	(0.079)	(0.060)	(0.060)	(0.051)	(0.064)	(0.202)
Observations	398,880	6,001	9,747	16,895	29,032	58,130	61,164	101,387	89,475	16,509
R-squared	0.102	0.032	0.031	0.045	0.079	0.101	0.114	0.110	0.107	0.093
Number of team1id	4,923	70	104	188	325	620	777	1,808	2,784	821
Adjusted R-squared	0.0908	0.0178	0.0185	0.0336	0.0676	0.0909	0.103	0.0941	0.0781	0.0448

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table. 2.11. Away Goals (original Football Foundation), with controls and fixed effects

VARIABLES	(1) All Steps Away Goals	(2) Step 1 Away Goals	(3) Step 2 Away Goals	(4) Step 3 Away Goals	(5) Step 4 Away Goals	(6) Step 5 Away Goals	(7) Step 6 Away Goals	(8) Step 7 Away Goals	(9) Step 8 Away Goals	(10) Step 9 Away Goals
FF 3G Pitch for Match	-0.014	-0.158	0.030	0.027	-0.068	0.101*	0.014	-0.248**	-0.490***	1.732
	(0.023)	(0.175)	(0.065)	(0.053)	(0.052)	(0.056)	(0.068)	(0.102)	(0.146)	(1.803)
Elopredict	-1.627***	-0.459**	-0.770***	-1.133***	-1.026***	-1.525***	-1.510***	-1.857***	-2.049***	-1.823***
	(0.028)	(0.229)	(0.157)	(0.123)	(0.082)	(0.067)	(0.062)	(0.056)	(0.078)	(0.219)
League Position (Home)	0.018***	0.002	0.003	0.001	0.009***	0.015***	0.021***	0.025***	0.030***	0.033***
	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)
League Position (Away)	-0.043***	-0.014***	-0.014***	-0.016***	-0.022***	-0.033***	-0.044***	-0.056***	-0.074***	-0.093***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)
Total goals (Home)	-0.001***	-0.000	-0.001*	-0.001	-0.002***	-0.002***	-0.001***	-0.002***	-0.002***	-0.003***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Total Goal Diff (Home)	-0.009***	-0.005***	-0.004***	-0.006***	-0.006***	-0.005***	-0.006***	-0.007***	-0.006***	-0.004***
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Constant	2.838***	1.674***	1.885***	2.143***	2.180***	2.662***	2.817***	3.026***	3.336***	3.634***
	(0.018)	(0.137)	(0.102)	(0.078)	(0.056)	(0.044)	(0.044)	(0.038)	(0.050)	(0.161)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626	93,782	17,311
R-squared	0.079	0.018	0.023	0.036	0.047	0.074	0.091	0.083	0.077	0.070
Number of team1id	4,937	70	104	188	325	624	777	1,810	2,788	821
Adjusted R-squared	0.0683	0.00439	0.0109	0.0244	0.0356	0.0637	0.0793	0.0670	0.0488	0.0224

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and weekday

Table 2.12. Goal difference (between clubs in the match that takes place, (original Football Foundation)), with controls and fixed effects

VARIABLES	(1) All Steps Goal Difference	(2) Step 1 Goal Difference	(3) Step 2 Goal Difference	(4) Step 3 Goal Difference	(5) Step 4 Goal Difference	(6) Step 5 Goal Difference	(7) Step 6 Goal Difference	(8) Step 7 Goal Difference	(9) Step 8 Goal Difference	(10) Step 9 Goal Difference
FF 3G Pitch for Match	0.260***	0.345	0.008	0.230***	0.368***	0.343***	0.104	0.917***	3.505***	-1.691
	(0.037)	(0.259)	(0.098)	(0.081)	(0.079)	(0.087)	(0.108)	(0.161)	(0.230)	(2.829)
Elopredict	3.600***	1.071***	1.858***	2.381***	2.352***	3.329***	3.500***	4.126***	4.715***	4.370***
	(0.044)	(0.340)	(0.238)	(0.186)	(0.126)	(0.104)	(0.097)	(0.089)	(0.122)	(0.344)
League Position (Home)	-0.043***	-0.009*	-0.005	-0.005	-0.017***	-0.029***	-0.042***	-0.049***	-0.057***	-0.062***
	(0.001)	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.010)
League Position (Away)	0.106***	0.037***	0.031***	0.043***	0.065***	0.085***	0.106***	0.141***	0.179***	0.219***
	(0.001)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.007)
Total Goals Scored (Home)	-0.001***	-0.001	-0.001	-0.000	0.001*	0.001	-0.000	-0.001	-0.001**	-0.003**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Total Goal Difference (Home)	0.017***	0.008***	0.010***	0.011***	0.011***	0.009***	0.012***	0.013***	0.011***	0.007***
	(0.000)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Constant	-2.115***	-0.572***	-0.881***	-1.525***	-1.581***	-2.150***	-2.353***	-2.620***	-3.084***	-3.237***
	(0.029)	(0.202)	(0.153)	(0.119)	(0.086)	(0.068)	(0.069)	(0.060)	(0.078)	(0.252)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626	93,782	17,311
R-squared	0.145	0.046	0.045	0.069	0.105	0.140	0.163	0.155	0.146	0.130
Number of team1id	4,937	70	104	188	325	624	777	1,810	2,788	821
Adjusted R-squared	0.134	0.0321	0.0335	0.0578	0.0951	0.131	0.152	0.140	0.119	0.0862

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and weekday

Table 2.13. Outcome Home win (original Football Foundation), with controls and fixed effects

VARIABLES	(1) All Steps Home Win	(2) Step 1 Home Win	(3) Step 2 Home Win	(4) Step 3 Home Win	(5) Step 4 Home Win	(6) Step 5 Home Win	(7) Step 6 Home Win	(8) Step 7 Home Win	(9) Step 8 Home Win	(10) Step 9 Home Win
FF 3G Pitch for Match	0.029***	0.013	-0.063**	0.038*	0.066***	0.054***	0.007	0.140***	0.197***	-0.218
	(0.007)	(0.077)	(0.027)	(0.021)	(0.019)	(0.019)	(0.021)	(0.030)	(0.040)	(0.454)
Elopredict	0.526***	0.306***	0.478***	0.472***	0.459***	0.529***	0.526***	0.519***	0.567***	0.463***
	(0.008)	(0.099)	(0.065)	(0.048)	(0.030)	(0.022)	(0.019)	(0.017)	(0.021)	(0.057)
League Position (Home)	-0.006***	0.000	0.004**	0.001	-0.002*	0.000	-0.004***	-0.002***	-0.003***	-0.001
	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
League Position (Away)	0.017***	0.009***	0.007***	0.009***	0.012***	0.015***	0.017***	0.022***	0.025***	0.028***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Goal Scored per game (Home)	0.008***	-0.006	0.009	0.019	0.017*	-0.006	-0.004	-0.006*	-0.003	-0.027***
	(0.002)	(0.025)	(0.018)	(0.013)	(0.009)	(0.006)	(0.005)	(0.003)	(0.003)	(0.008)
Goal Diff per game (Home)	0.037***	0.047**	0.065***	0.034***	0.043***	0.059***	0.042***	0.042***	0.031***	0.032***
	(0.001)	(0.021)	(0.014)	(0.011)	(0.007)	(0.004)	(0.003)	(0.002)	(0.002)	(0.005)
Constant	0.068***	0.182**	0.079	0.031	0.029	0.013	0.030*	0.019	-0.003	0.071
	(0.007)	(0.072)	(0.052)	(0.038)	(0.026)	(0.018)	(0.017)	(0.013)	(0.016)	(0.046)
Observations	398,880	6,001	9,747	16,895	29,032	58,130	61,164	101,387	89,475	16,509
R-squared	0.100	0.031	0.034	0.041	0.071	0.094	0.111	0.101	0.095	0.082
Number of team1id	4,923	70	104	188	325	620	777	1,808	2,784	821
Adjusted R-squared	0.0888	0.0168	0.0222	0.0296	0.0595	0.0838	0.0991	0.0846	0.0660	0.0330

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and weekday

In Table 2.9. we can see there are positive effects of having a 3G pitch through the top 5 Steps for log attendance ranging from a 7-13% increase across these Steps, even with our Uncertainty of Outcome variables included. There is also a large coefficient for those at Step 8 but in this Step as we can see from the much lower number of observations (less than $^{1}/_{5}$) of Step 6, this is because attendance is poorly recorded and is only one level above 'park football' where there would be minimal facilities. We can see that the Uncertainty of Outcome test via our Elo ratings and thus expected home win cannot be ruled out as a factor in helping fans decide on whether to attend a match at this level. League position has a negative coefficient because the highest value would be the lowest placed clubs (20-24) with 1 being the highest placed clubs but 'lowest' value. The competitiveness of a match clearly having some interest to fans.

In Table 2.10., where home goals are the dependent variable, we can see that having a 3G pitch may be worth up to two goals per season for the first two steps, then increasing for the next 4 steps up to nearly 4.5 goals per season. The effect drops off in Step 6, and then increases up to 7 goals per season at Step 7 this may be down to the lower proportion of 3G clubs in that step though. We do find that the control variables also have some value in predicting goals for the home club, which is to be expected as the Elo rating plus other various form guides such as league position and goal difference would indicate that. In Table 2.11., displaying away goals and there appears to be a much smaller inconsistent effect here. Table 2.12. on the other hand shows in some of the lower league quite a difference in goal difference. In the match outcome, regression Tables we can see with match 'Outcomes' (Tables 2.13-2.15.) that whilst there isn't a great deal of effect on a defeat or draw, there may some small effect on a win, the most interesting being that the coefficient increase as the Step increases, with a greater effect being at the lowest level (where if it is an effect it is likely to be down to ability being at the lowest level in the dataset). The overall issue with this section however is that the data here suffers from the selection bias question we mention in the introduction to this Chapter, as the later results will show, when clubs are tracked across all Steps where there are clubs with 3G pitches of both types, the effects on attendance and performance are reduced. This indicates that the larger dataset gives the more complete information.

Table 2.16. Log Attendance for 3G pitches (Clubs with any kind of 3G pitch – for use in competitive matches or for training purposes only), with controls and fixed effects and Uncertainty of Outcome test

VARIABLES	(1) All Steps Log Attendance	(2) Step 1 Log Attendance	(3) Step 2 Log Attendance	(4) Step 3 Log Attendance	(5) Step 4 Log Attendance	(6) Step 5 Log Attendance	(7) Step 6 Log Attendance	(8) Step 7 Log Attendance	(9) Step 8 Log Attendance
3G Training and Match Use	0.001	-0.002	-0.006	0.010	0.006	0.006	0.001	-0.063	0.167
	(0.007)	(0.028)	(0.016)	(0.013)	(0.012)	(0.013)	(0.019)	(0.074)	(0.196)
Elo Prediction	-0.302***	-2.237***	-1.262***	-1.896***	-1.095***	-0.947***	-0.420***	-0.433**	0.112
	(0.047)	(0.400)	(0.253)	(0.173)	(0.099)	(0.085)	(0.074)	(0.180)	(0.649)
Elo Prediction^2	0.328***	2.284***	1.116***	1.639***	0.990***	0.743***	0.261***	0.350**	-0.148
	(0.046)	(0.396)	(0.252)	(0.172)	(0.098)	(0.083)	(0.073)	(0.173)	(0.637)
Goals Scored (Home)	-0.005***	-0.003***	-0.002***	-0.003***	-0.003***	-0.005***	-0.004***	-0.005***	-0.008***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Goals Scored (Away)	0.005***	0.004***	0.004***	0.005***	0.005***	0.005***	0.004***	0.004***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Goal Difference (Home)	0.004***	0.005***	0.006***	0.006***	0.005***	0.005***	0.005***	0.004***	0.005***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
League Position (Home)	-0.005***	-0.013***	-0.011***	-0.010***	-0.009***	-0.011***	-0.009***	-0.010***	-0.009*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.005)
Constant	4.725***	7.967***	6.737***	6.248***	5.277***	4.783***	4.326***	4.126***	3.841***
	(0.014)	(0.106)	(0.068)	(0.047)	(0.028)	(0.025)	(0.022)	(0.055)	(0.171)
Observations	187,148	5,722	9,584	17,338	29,779	56,355	54,634	10,122	1,473
R-squared	0.156	0.251	0.189	0.176	0.215	0.158	0.160	0.145	0.096
Number of team1id	1,566	70	104	188	325	622	757	320	171
Adjusted R-squared	0.149	0.239	0.179	0.166	0.206	0.148	0.148	0.115	-0.0343

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and weekday

Table 2.17. Home Goals (Clubs with any kind of 3G pitch – for use in competitive matches or for training purposes only), with controls and fixed effects

VARIABLES	(1) All Steps Home Goals	(2) Step 1 Home Goals	(3) Step 2 Home Goals	(4) Step 3 Home Goals	(5) Step 4 Home Goals	(6) Step 5 Home Goals	(7) Step 6 Home Goals	(8) Step 7 Home Goals	(9) Step 8 Home Goals	(10) Step 9 Home Goals
3G Training and match use	-0.026	0.005	-0.141**	-0.000	-0.056	-0.014	-0.036	0.164*	-0.107	0.104
	(0.026)	(0.117)	(0.062)	(0.051)	(0.047)	(0.049)	(0.067)	(0.091)	(0.149)	(0.277)
Elopredict	2.001***	0.664***	1.162***	1.280***	1.374***	1.754***	1.937***	2.200***	2.525***	2.352***
	(0.032)	(0.257)	(0.175)	(0.134)	(0.092)	(0.074)	(0.070)	(0.065)	(0.089)	(0.250)
League Position (Home)	-0.016***	-0.007	0.004	0.001	-0.004	0.001	-0.008***	-0.010***	-0.013***	-0.016*
	(0.001)	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.009)
League Position (Away)	0.065***	0.024***	0.017***	0.027***	0.043***	0.054***	0.064***	0.089***	0.111***	0.133***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.005)
Goal Scored per game (Home)	0.136***	-0.052	0.059	0.034	0.121***	0.054***	0.087***	0.048***	-0.002	-0.116***
	(0.006)	(0.064)	(0.047)	(0.035)	(0.027)	(0.018)	(0.017)	(0.013)	(0.013)	(0.034)
Goal Diff per game (Home)	0.092***	0.068	0.101***	0.092***	0.069***	0.134***	0.102***	0.107***	0.095***	0.100***
	(0.004)	(0.054)	(0.039)	(0.029)	(0.021)	(0.013)	(0.012)	(0.009)	(0.009)	(0.024)
Constant	0.350***	1.129***	0.768***	0.504***	0.347***	0.240***	0.147**	0.133***	0.096	0.406**
	(0.024)	(0.185)	(0.140)	(0.105)	(0.079)	(0.060)	(0.060)	(0.051)	(0.064)	(0.200)
Observations	398,880	6,001	9,747	16,895	29,032	58,130	61,164	101,387	89,475	16,509
R-squared	0.102	0.032	0.031	0.044	0.078	0.100	0.114	0.110	0.103	0.093
Number of team1id	4,923	70	104	188	325	620	777	1,808	2,784	821
Adjusted R-squared	0.0903	0.0177	0.0190	0.0325	0.0668	0.0900	0.103	0.0938	0.0745	0.0448

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 2.18. Away Goals (Clubs with any kind of 3G pitch – for use in competitive matches or for training purposes only), with controls and fixed effects

VARIABLES	(1) All Steps Away Goals	(2) Step 1 Away Goals	(3) Step 2 Away Goals	(4) Step 3 Away Goals	(5) Step 4 Away Goals	(6) Step 5 Away Goals	(7) Step 6 Away Goals	(8) Step 7 Away Goals	(9) Step 8 Away Goals	(10) Step 9 Away Goals
3G Training and match use	-0.017	0.070	0.020	-0.021	0.058	-0.121***	-0.032	0.085	-0.069	-0.264
	(0.023)	(0.103)	(0.056)	(0.046)	(0.042)	(0.044)	(0.060)	(0.079)	(0.131)	(0.249)
Elopredict	-1.627***	-0.460**	-0.769***	-1.132***	-1.031***	-1.524***	-1.510***	-1.856***	-2.044***	-1.815***
	(0.028)	(0.229)	(0.157)	(0.123)	(0.082)	(0.067)	(0.062)	(0.056)	(0.078)	(0.219)
League Position (Home)	0.018***	0.002	0.003	0.001	0.009***	0.015***	0.021***	0.025***	0.030***	0.033***
	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)
League Position (Away)	-0.043***	-0.014***	-0.014***	-0.016***	-0.022***	-0.033***	-0.044***	-0.056***	-0.074***	-0.093***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)
Total Goals Scored (Home)	-0.001***	-0.000	-0.001*	-0.001	-0.002***	-0.002***	-0.001***	-0.002***	-0.002***	-0.003***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Total Goal Difference (Home)	-0.009***	-0.005***	-0.004***	-0.006***	-0.006***	-0.005***	-0.006***	-0.007***	-0.006***	-0.004***
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Constant	2.838***	1.659***	1.883***	2.149***	2.171***	2.673***	2.819***	3.020***	3.332***	3.657***
	(0.018)	(0.136)	(0.102)	(0.078)	(0.056)	(0.044)	(0.044)	(0.038)	(0.050)	(0.159)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626	93,782	17,311
R-squared	0.079	0.018	0.023	0.036	0.047	0.074	0.091	0.083	0.077	0.070
Number of team1id	4,937	70	104	188	325	624	777	1,810	2,788	821
Adjusted R-squared	0.0683	0.00433	0.0109	0.0244	0.0357	0.0638	0.0793	0.0669	0.0487	0.0224

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 2.19. Goal difference, between clubs in the match that takes place (Clubs with any kind of 3G pitch – for use in competitive matches or for training purposes only), with controls and fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All Steps	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6	Step 7	Step 8	Step 9
VARIABLES	Goal Difference	Goal Difference	Goal Difference	Goal Difference	Goal Difference	Goal Difference	Goal Difference	Goal Difference	Goal Difference	Goal Difference
3G Training and match use	-0.012	-0.056	-0.157*	0.015	-0.117*	0.111	-0.009	0.023	0.011	0.378
	(0.036)	(0.153)	(0.085)	(0.069)	(0.065)	(0.069)	(0.094)	(0.124)	(0.206)	(0.390)
Elopredict	3.603***	1.075***	1.860***	2.394***	2.373***	3.335***	3.499***	4.123***	4.683***	4.360***
	(0.044)	(0.340)	(0.238)	(0.186)	(0.126)	(0.104)	(0.097)	(0.089)	(0.122)	(0.344)
League Position (Home)	-0.043***	-0.009*	-0.005	-0.005	-0.017***	-0.029***	-0.042***	-0.049***	-0.057***	-0.061***
	(0.001)	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.010)
League Position (Away)	0.106***	0.037***	0.031***	0.042***	0.065***	0.085***	0.106***	0.141***	0.180***	0.219***
	(0.001)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.007)
Total Goals Scored (Home)	-0.001***	-0.001	-0.001	-0.001	0.001*	0.001	-0.000	-0.001*	-0.001**	-0.003**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Total Goal Difference (Home)	0.017***	0.008***	0.010***	0.011***	0.011***	0.009***	0.012***	0.013***	0.011***	0.007***
	(0.000)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Constant	-2.105***	-0.542***	-0.862***	-1.497***	-1.544***	-2.138***	-2.345***	-2.606***	-3.047***	-3.262***
	(0.029)	(0.202)	(0.154)	(0.119)	(0.086)	(0.068)	(0.069)	(0.060)	(0.078)	(0.250)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626	93,782	17,311
R-squared	0.145	0.046	0.046	0.068	0.105	0.140	0.163	0.155	0.143	0.130
Number of team1id	4,937	70	104	188	325	624	777	1,810	2,788	821
Adjusted R-squared	0.134	0.0318	0.0338	0.0573	0.0946	0.131	0.152	0.140	0.117	0.0863

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 2.20. Outcome Home Win (Clubs with any kind of 3G pitch – for use in competitive matches or for training purposes only), with controls and fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All Steps	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6	Step 7	Step 8	Step 9
VARIABLES	Outcome Home Win	Outcome Home Win	Outcome Home Win	Outcome Home Win	Outcome Home Win	Outcome Home Win	Outcome Home Win	Outcome Home Win	Outcome Home Win	Outcome Home Win
3G Training and match use	0.004	-0.009	-0.037	0.017	-0.014	0.019	0.020	0.010	-0.007	0.062
	(0.007)	(0.045)	(0.023)	(0.018)	(0.016)	(0.015)	(0.019)	(0.023)	(0.036)	(0.063)
Elopredict	0.526***	0.306***	0.473***	0.475***	0.463***	0.530***	0.526***	0.519***	0.565***	0.462***
	(0.008)	(0.099)	(0.065)	(0.048)	(0.030)	(0.022)	(0.019)	(0.017)	(0.021)	(0.057)
League Position (Home)	-0.006***	0.000	0.004**	0.001	-0.002*	-0.000	-0.004***	-0.002***	-0.003***	-0.001
	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
League Position (Away)	0.017***	0.009***	0.007***	0.009***	0.012***	0.015***	0.017***	0.022***	0.025***	0.028***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Goal Scored per game (Home)	0.008***	-0.006	0.005	0.020	0.018**	-0.006	-0.004	-0.006*	-0.003	-0.027***
	(0.002)	(0.025)	(0.018)	(0.013)	(0.009)	(0.006)	(0.005)	(0.003)	(0.003)	(0.008)
Goal Diff per game (Home)	0.037***	0.047**	0.065***	0.034***	0.043***	0.058***	0.042***	0.042***	0.031***	0.032***
	(0.001)	(0.021)	(0.014)	(0.011)	(0.007)	(0.004)	(0.003)	(0.002)	(0.002)	(0.005)
Constant	0.069***	0.183**	0.086*	0.031	0.033	0.014	0.029*	0.020	-0.001	0.067
	(0.007)	(0.072)	(0.052)	(0.038)	(0.026)	(0.018)	(0.017)	(0.013)	(0.016)	(0.045)
Observations	398,880	6,001	9,747	16,895	29,032	58,130	61,164	101,387	89,475	16,509
R-squared	0.100	0.031	0.034	0.041	0.070	0.094	0.111	0.101	0.095	0.082
Number of team1id	4,923	70	104	188	325	620	777	1,808	2,784	821
Adjusted R-squared	0.0887	0.0168	0.0219	0.0295	0.0591	0.0837	0.0992	0.0844	0.0657	0.0331

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

If we then look at the results from the clubs with any kind of 3G pitch the noticeable result, is that the effects of a 3G pitch are quire drastically reduced. Something that is continuous throughout the regressions in tables 2.16.-2.22. is that our Elo ratings are a consistent predictor, it's always significant expect in Step 8, whether reflecting home or away club performance. Home League Position is significant in terms of being linked to attendance but is not as strong a predictor of home goals. Thus, with Home League Position and the Elo ratings, it seems that home win probability it likely to be a stronger predictor of attendance than whether a team has one of this larger group of 3G pitches.

As discussed, this difference when compared to the first set of regressions for 3G pitches in tables 2.9-2.15. is likely to be a sample selection effect, that by including less successful clubs (i.e. clubs that may have fallen out of the top 6 Steps by 2022), would naturally lead to a slight disintegration or dispersion of the overall effect of what are likely to be stronger clubs. We also now have over 270 clubs in the section of 'clubs with a 3G Practice pitch and Match Pitch', and more clubs as a whole with 'match pitch use' only, with many of these clubs coming from Steps 7-9 but also now includes those that may have made it to Step 5 or 6 for only one or two seasons, or indeed may have been relegated early on in the period and struggled since.

There appears to still be some value to having a 3G pitch for either practice purposes or for match use, particularly at Step 7, where although often the regressions show no significance, the coefficients are positive indicating that the benefits may be there but quite marginal (This is the case in both Tables 2.23 and 2.30. where we have used Log attendance as the main dependent variable). We might expect this as player quality is lower at Step 7 than higher steps. A 3G pitch appears to help with home goals at Steps 7 & 9 but for the rest, it doesn't seem to be aiding goal scoring performance. What does happen though to counteract this slightly is that the effect of having a 3g pitch appears to be more evident in suppressing away goals, as we see in Table 2.18. where although not significant, there is a negative coefficient to the effect of 1-2 goals per season across all steps. This then *is* significant at Step 5, a crucial mid-point between those clubs that are really confined to their county or town at Steps 7-9 and those that are just below professional and semi-professional at Steps 2-4.

Somewhat confusingly, goal difference becomes a bit more problematic to assess, as there is some statistical significance in the coefficients in the top 3-4 Steps but the coefficient is negative. This inconsistency is also seen in the match ‘outcome’ regressions, where having a practice pitch or using it for matches seems to be of no real positive effect in the higher steps but the coefficients in the lower Steps have enough positivity to suggest there is some value. This is strengthened by the fact there appears to be a negative effect on away wins at Steps 5 and 6, although less so at Steps 7 & 8 where the effect is lost.

In Tables 2.23-2.29. we remove the clubs that have a 3G pitch for training purposes only and focus exclusively on those clubs that use this type of pitch for competitive matches. This means that compared to the regressions in Tables 2.16-2.22. we now have in this section, all the clubs that have or had a 3G pitch in any of the matches between 2011-2022, or any club that played within the non-league structure during this period. We still see a reduced effect when compared to the original more positive looking regressions, again indicating that the selection bias of only using clubs within the top 6 Steps gives a false picture and too optimistic an impression of the effect of 3G pitches.

Table 2.23. Log Attendance for 3G pitches (Clubs with 'Match use' 3G pitches only), with controls and fixed effects and Uncertainty of Outcome test.

VARIABLES	(1) All Steps Log Attendance	(2) Step 1 Log Attendance	(3) Step 2 Log Attendance	(4) Step 3 Log Attendance	(5) Step 4 Log Attendance	(6) Step 5 Log Attendance	(7) Step 6 Log Attendance	(8) Step 7 Log Attendance	(9) Step 8 Log Attendance
Match Use pitch Only	-0.003	-0.002	-0.004	0.005	0.003	-0.003	-0.011	-0.020	0.164
	(0.006)	(0.028)	(0.014)	(0.012)	(0.011)	(0.012)	(0.017)	(0.066)	(0.186)
Elo Prediction	-0.302***	-2.237***	-1.262***	-1.896***	-1.095***	-0.947***	-0.420***	-0.433**	0.113
	(0.047)	(0.400)	(0.253)	(0.173)	(0.099)	(0.085)	(0.074)	(0.180)	(0.649)
Elo Prediction^2	0.328***	2.284***	1.117***	1.639***	0.990***	0.743***	0.261***	0.351**	-0.148
	(0.046)	(0.396)	(0.252)	(0.172)	(0.098)	(0.083)	(0.073)	(0.173)	(0.636)
Goals Scored (Home)	-0.005***	-0.003***	-0.002***	-0.003***	-0.003***	-0.005***	-0.004***	-0.005***	-0.008***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Goals Scored (Away)	0.005***	0.004***	0.004***	0.005***	0.005***	0.005***	0.004***	0.004***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Goal Difference (Home)	0.004***	0.005***	0.006***	0.006***	0.005***	0.005***	0.005***	0.004***	0.005***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
League Position (Home)	-0.005***	-0.013***	-0.011***	-0.010***	-0.009***	-0.011***	-0.009***	-0.010***	-0.008*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.005)
Constant	4.725***	7.967***	6.737***	6.249***	5.277***	4.784***	4.326***	4.125***	3.840***
	(0.014)	(0.106)	(0.068)	(0.047)	(0.028)	(0.025)	(0.022)	(0.055)	(0.171)
Observations	187,148	5,722	9,584	17,338	29,779	56,355	54,634	10,122	1,473
R-squared	0.156	0.251	0.189	0.176	0.215	0.158	0.160	0.145	0.096
Number of team1id	1,566	70	104	188	325	622	757	320	171
Adjusted R-squared	0.149	0.239	0.179	0.166	0.206	0.148	0.148	0.115	-0.0343

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 2.24. Home Goals (Clubs with 'Match use' 3G pitches only), with controls and fixed effects

VARIABLES	(1) All Steps Home Goals	(2) Step 1 Home Goals	(3) Step 2 Home Goals	(4) Step 3 Home Goals	(5) Step 4 Home Goals	(6) Step 5 Home Goals	(7) Step 6 Home Goals	(8) Step 7 Home Goals	(9) Step 8 Home Goals	(10) Step 9 Home Goals
Match Use only Pitch	-0.013	0.005	-0.075	-0.020	-0.072*	-0.008	-0.029	0.150*	0.078	0.187
	(0.024)	(0.117)	(0.055)	(0.046)	(0.043)	(0.046)	(0.061)	(0.080)	(0.118)	(0.244)
Elopredict	1.995***	0.664***	1.162***	1.280***	1.374***	1.754***	1.937***	2.200***	2.525***	2.351***
	(0.032)	(0.257)	(0.175)	(0.134)	(0.092)	(0.074)	(0.070)	(0.065)	(0.089)	(0.250)
League Position (Home)	-0.015***	-0.007	0.004	0.001	-0.004	0.001	-0.008***	-0.010***	-0.013***	-0.016*
	(0.001)	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.009)
League Position (Away)	0.065***	0.024***	0.017***	0.027***	0.043***	0.054***	0.064***	0.089***	0.111***	0.133***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.005)
Goal Scored per game (Home)	0.134***	-0.052	0.059	0.034	0.121***	0.054***	0.087***	0.048***	-0.002	-0.116***
	(0.006)	(0.064)	(0.047)	(0.035)	(0.027)	(0.018)	(0.017)	(0.013)	(0.013)	(0.034)
Goal Diff per game (Home)	0.094***	0.068	0.101***	0.092***	0.069***	0.134***	0.102***	0.107***	0.095***	0.100***
	(0.004)	(0.054)	(0.039)	(0.029)	(0.021)	(0.013)	(0.012)	(0.009)	(0.009)	(0.024)
Constant	0.289***	1.128***	0.766***	0.507***	0.350***	0.240***	0.147**	0.132***	0.093	0.404**
	(0.024)	(0.186)	(0.140)	(0.105)	(0.079)	(0.060)	(0.060)	(0.051)	(0.064)	(0.200)
Observations	398,880	6,001	9,747	16,895	29,032	58,130	61,164	101,387	89,475	16,509
R-squared	0.102	0.032	0.031	0.044	0.078	0.100	0.114	0.110	0.103	0.093
Number of team1id	4,923	70	104	188	325	620	777	1,808	2,784	821
Adjusted R-squared	0.0906	0.0177	0.0187	0.0325	0.0668	0.0900	0.103	0.0938	0.0745	0.0449

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 2.25. Away Goals (Clubs with ‘Match use’ 3G pitches only), with controls and fixed effects

VARIABLES	(1) All Steps Away Goals	(2) Step 1 Away Goals	(3) Step 2 Away Goals	(4) Step 3 Away Goals	(5) Step 4 Away Goals	(6) Step 5 Away Goals	(7) Step 6 Away Goals	(8) Step 7 Away Goals	(9) Step 8 Away Goals	(10) Step 9 Away Goals
Match Use only Pitch	-0.023	0.070	0.022	-0.053	0.037	-0.114***	-0.021	0.104	-0.079	-0.316
	(0.021)	(0.103)	(0.049)	(0.041)	(0.039)	(0.042)	(0.055)	(0.070)	(0.104)	(0.217)
Elopredict	-1.627***	-0.460**	-0.769***	-1.132***	-1.030***	-1.524***	-1.510***	-1.856***	-2.045***	-1.813***
	(0.028)	(0.229)	(0.157)	(0.123)	(0.082)	(0.067)	(0.062)	(0.056)	(0.078)	(0.219)
League Position (Home)	0.018***	0.002	0.003	0.001	0.009***	0.015***	0.021***	0.025***	0.030***	0.033***
	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)
League Position (Away)	-0.043***	-0.014***	-0.014***	-0.016***	-0.022***	-0.033***	-0.044***	-0.056***	-0.074***	-0.093***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)
Total Goals Scored (Home)	-0.001***	-0.000	-0.001*	-0.001	-0.002***	-0.002***	-0.001***	-0.002***	-0.002***	-0.003***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Total Goal Difference (Home)	-0.009***	-0.005***	-0.004***	-0.006***	-0.006***	-0.005***	-0.006***	-0.007***	-0.006***	-0.004***
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Constant	2.839***	1.650***	1.882***	2.156***	2.171***	2.674***	2.819***	3.019***	3.332***	3.660***
	(0.018)	(0.137)	(0.102)	(0.078)	(0.056)	(0.044)	(0.044)	(0.038)	(0.050)	(0.159)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626	93,782	17,311
R-squared	0.079	0.018	0.023	0.036	0.047	0.074	0.091	0.083	0.077	0.070
Number of team1id	4,937	70	104	188	325	624	777	1,810	2,788	821
Adjusted R-squared	0.0683	0.00433	0.0109	0.0245	0.0356	0.0638	0.0793	0.0669	0.0487	0.0225

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 2.26. Goal difference, between clubs in the match that takes place (Clubs with ‘Match use’ 3G pitches only), with controls and fixed effects

VARIABLES	(1) All Steps Goal Difference	(2) Step 1 Goal Difference	(3) Step 2 Goal Difference	(4) Step 3 Goal Difference	(5) Step 4 Goal Difference	(6) Step 5 Goal Difference	(7) Step 6 Goal Difference	(8) Step 7 Goal Difference	(9) Step 8 Goal Difference	(10) Step 9 Goal Difference
Match Use only Pitch	0.003	-0.056	-0.098	0.033	-0.115*	0.106	-0.014	0.003	0.154	0.509
	(0.033)	(0.153)	(0.075)	(0.063)	(0.060)	(0.065)	(0.086)	(0.110)	(0.163)	(0.341)
Elopredict	3.603***	1.075***	1.859***	2.394***	2.373***	3.334***	3.499***	4.123***	4.684***	4.357***
	(0.044)	(0.340)	(0.238)	(0.186)	(0.126)	(0.104)	(0.097)	(0.089)	(0.122)	(0.344)
League Position (Home)	-0.043***	-0.009*	-0.005	-0.005	-0.017***	-0.029***	-0.042***	-0.049***	-0.057***	-0.061***
	(0.001)	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.010)
League Position (Away)	0.106***	0.037***	0.031***	0.042***	0.065***	0.085***	0.106***	0.141***	0.180***	0.219***
	(0.001)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.007)
Total Goals Scored (Home)	-0.001***	-0.001	-0.001	-0.001	0.001*	0.001	-0.000	-0.001*	-0.001**	-0.003**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Total Goal Difference (Home)	0.017***	0.008***	0.010***	0.011***	0.011***	0.009***	0.012***	0.013***	0.011***	0.007***
	(0.000)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Constant	-2.106***	-0.536***	-0.863***	-1.501***	-1.541***	-2.139***	-2.345***	-2.605***	-3.050***	-3.266***
	(0.029)	(0.203)	(0.154)	(0.119)	(0.086)	(0.068)	(0.069)	(0.060)	(0.079)	(0.250)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626	93,782	17,311
R-squared	0.145	0.046	0.045	0.068	0.105	0.140	0.163	0.155	0.143	0.131
Number of team1id	4,937	70	104	188	325	624	777	1,810	2,788	821
Adjusted R-squared	0.134	0.0318	0.0337	0.0573	0.0946	0.131	0.152	0.140	0.117	0.0863

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 2.27. Outcome Home Win (Clubs with ‘Match use’ 3G pitches only), with controls and fixed effects

VARIABLES	(1) All Steps Outcome Home Win	(2) Step 1 Outcome Home Win	(3) Step 2 Outcome Home Win	(4) Step 3 Outcome Home Win	(5) Step 4 Outcome Home Win	(6) Step 5 Outcome Home Win	(7) Step 6 Outcome Home Win	(8) Step 7 Outcome Home Win	(9) Step 8 Outcome Home Win	(10) Step 9 Outcome Home Win
Match Use only Pitch	0.004	-0.009	-0.026	0.025	-0.027*	0.024*	0.010	0.007	0.007	0.043
	(0.006)	(0.045)	(0.021)	(0.016)	(0.014)	(0.014)	(0.017)	(0.021)	(0.028)	(0.055)
Elopredict	0.526***	0.306***	0.473***	0.475***	0.463***	0.530***	0.526***	0.519***	0.565***	0.462***
	(0.008)	(0.099)	(0.065)	(0.048)	(0.030)	(0.022)	(0.019)	(0.017)	(0.021)	(0.057)
League Position (Home)	-0.006***	0.000	0.004**	0.001	-0.002*	-0.000	-0.004***	-0.002***	-0.003***	-0.001
	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
League Position (Away)	0.017***	0.009***	0.007***	0.009***	0.012***	0.015***	0.017***	0.022***	0.025***	0.028***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Goal Scored per game (Home)	0.008***	-0.006	0.005	0.020	0.018**	-0.006	-0.004	-0.006*	-0.003	-0.027***
	(0.002)	(0.025)	(0.018)	(0.013)	(0.009)	(0.006)	(0.005)	(0.003)	(0.003)	(0.008)
Goal Diff per game (Home)	0.037***	0.047**	0.065***	0.034***	0.043***	0.058***	0.042***	0.042***	0.031***	0.032***
	(0.001)	(0.021)	(0.014)	(0.011)	(0.007)	(0.004)	(0.003)	(0.002)	(0.002)	(0.005)
Constant	0.069***	0.184**	0.087*	0.029	0.034	0.014	0.030*	0.020	-0.001	0.067
	(0.007)	(0.072)	(0.052)	(0.038)	(0.026)	(0.018)	(0.017)	(0.013)	(0.016)	(0.045)
Observations	398,880	6,001	9,747	16,895	29,032	58,130	61,164	101,387	89,475	16,509
R-squared	0.100	0.031	0.034	0.041	0.070	0.094	0.111	0.101	0.095	0.082
Number of team1id	4,923	70	104	188	325	620	777	1,808	2,784	821
Adjusted R-squared	0.0887	0.0168	0.0218	0.0295	0.0592	0.0838	0.0991	0.0844	0.0657	0.0331

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

The summary of what happens in Table 2.23. though is that, similarly to Table 2.16., it is still only at Step 8 that around 16% can be added to attendances and this is not significant in the regressions. It is worth remembering at this point that so many games at this level do not have an accurate record of attendance, or it is not reported, or simply that the attendances are so low. The attendance effects are also very minimal, with the most being 0.01 or 0.02% effects negatively or less than 0.01% positively suggesting that the clubs using their pitches competitively only do not gain an attendance advantage outside of Step 8. We can also see that again our Elo ratings give strong indications that the main driver of attendance at this level is expected home win.

There appears to be a clear ‘quality’ issue in terms of the quality of clubs, in that a 3G pitch may add between 7 to 18 goals per season at steps 7-9 but if a club is either no longer in Step 7 or was not at all, then the effects are lost and in fact it seems to penalise a club to a marginal effect. As Jan Van Ours has pointed out (van Ours, 2019) it is likely that a pitch like this can benefit struggling clubs but that quite quickly quality starts to be a factor in terms of club strength over-riding any differential effect of the pitch.

The situation with away goals on match use pitches is slightly less consistent across all Steps. At Step 5 it appears that a 3G pitch could reduce away goals per season by up to 11 goals but this is the only Step where there is statistical significance.

For Goal difference, we find that there is a similar effect as with home goals, in that there are some consistent positive coefficients across Steps 7-9 in terms of a positive goal difference, but again that these results are not significant, so it is not possible to exclusively attribute the effect entirely due to the 3G pitch. That goal difference over the 2011-22 seasons appears to be both a positive and negative effect across different Steps tends to lend to the idea that we are measuring clubs that often may go up a Step or two over time but either will plateau or will also get relegated but something interesting does happen in Table 2.26. In Table 2.27., where we examine the effect on 'Home win' outcomes, in Step 3 and Steps 5-9 there appears to be a small increase in the likelihood of win. This seems to be very marginal (and it is likely that the 'power' of this is somewhat reduced by the number of seasons studied). This is slightly offset by the fact that for 'away wins' there seems to be an inconsistency that fits with the overall story of non-league football, that an away win for the club playing away when a 3G pitch is used (i.e. the opposition to the club with a 3G pitch) is more likely to win by around 2% at Step 4, whereas the opposite is the case at Step 5, where the home club is more likely to see an away defeat (hence the negative coefficient).

The overall outcome of these 3 sets of regressions, there is quite a mixed set of outcomes. At this point it is worth remembering that in terms of concentration of the spread of 3G pitches, the greater concentration on average per league, are at the higher Steps, where the effects of having a pitch are reduced. At the lowest levels where the least amount of pitches are available, it appears to have the greatest impact, although with attendances, generally speaking the lower the Step, the less accurate the attendance data will be. That that impact fades as clubs are more successful, either because other clubs get used to playing them with that pitch, or simply because as a club gets better, the advantage of having a 3G pitch softens and reduces its overall value.

Table 2.30. Log Attendance with 3G pitches (Both clubs with 3G pitch), with controls and fixed effects

VARIABLES	(1) All Steps Log Attendance	(2) Step 1 Log Attendance	(3) Step 2 Log Attendance	(4) Step 3 Log Attendance	(5) Step 4 Log Attendance	(6) Step 5 Log Attendance	(7) Step 6 Log Attendance	(8) Step 7 Log Attendance
Home and Away 3G	0.007	-0.097**	-0.020	-0.071***	0.007	0.092***	-0.032	-0.100
	(0.011)	(0.041)	(0.022)	(0.017)	(0.019)	(0.028)	(0.027)	(0.310)
Elopredict	0.187***	0.325***	0.074	0.002	0.109***	0.035*	-0.002	0.056
	(0.011)	(0.061)	(0.046)	(0.035)	(0.023)	(0.020)	(0.019)	(0.044)
League Position (Home)	-0.005***	-0.017***	-0.014***	-0.014***	-0.012***	-0.011***	-0.011***	-0.012***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
League Position (Away)	-0.013***	-0.009***	-0.009***	-0.011***	-0.013***	-0.014***	-0.012***	-0.013***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Goal Scored per game (Home)	-0.042***	0.043***	0.046***	0.006	0.006	0.004	-0.003	-0.008
	(0.003)	(0.015)	(0.013)	(0.009)	(0.007)	(0.005)	(0.005)	(0.009)
Goal Diff per game (Home)	0.043***	-0.008	0.010	0.017**	0.029***	0.033***	0.031***	0.014**
	(0.002)	(0.013)	(0.010)	(0.008)	(0.005)	(0.004)	(0.003)	(0.006)
Constant	4.787***	7.400***	6.466***	5.932***	5.136***	4.628***	4.300***	4.084***
	(0.009)	(0.044)	(0.037)	(0.027)	(0.020)	(0.016)	(0.016)	(0.037)
Observations	181,340	5,590	9,338	16,875	28,941	54,672	52,822	9,670
R-squared	0.163	0.261	0.192	0.175	0.217	0.162	0.162	0.149
Number of team1id	1,560	70	104	188	325	619	757	316
Adjusted R-squared	0.156	0.250	0.181	0.165	0.208	0.152	0.149	0.119

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 2.31. Home Goals with 3G pitches (Both clubs with 3G pitch), with controls and fixed effects

VARIABLES	(1) All Steps Home Goals	(2) Step 1 Home Goals	(3) Step 2 Home Goals	(4) Step 3 Home Goals	(5) Step 4 Home Goals	(6) Step 5 Home Goals	(7) Step 6 Home Goals	(8) Step 7 Home Goals
Home and Away 3G	-0.045	0.037	0.101	-0.097	-0.101	-0.060	0.060	0.102
	(0.043)	(0.174)	(0.084)	(0.065)	(0.077)	(0.103)	(0.104)	(0.255)
Elopredict	1.995***	0.666***	1.162***	1.281***	1.371***	1.754***	1.937***	2.200***
	(0.032)	(0.257)	(0.175)	(0.134)	(0.092)	(0.074)	(0.070)	(0.065)
League Position (Home)	-0.015***	-0.007	0.004	0.001	-0.004	0.001	-0.008***	-0.010***
	(0.001)	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
League Position (Away)	0.065***	0.024***	0.017***	0.027***	0.043***	0.054***	0.064***	0.089***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Goal Scored per game (Home)	0.134***	-0.052	0.060	0.034	0.120***	0.054***	0.087***	0.048***
	(0.006)	(0.064)	(0.047)	(0.035)	(0.027)	(0.018)	(0.017)	(0.013)
Goal Diff per game (Home)	0.094***	0.068	0.100**	0.092***	0.070***	0.134***	0.102***	0.107***
	(0.004)	(0.054)	(0.039)	(0.029)	(0.021)	(0.013)	(0.012)	(0.009)
Constant	0.289***	1.128***	0.750***	0.507***	0.345***	0.240***	0.145**	0.136***
	(0.024)	(0.185)	(0.140)	(0.105)	(0.079)	(0.060)	(0.060)	(0.051)
Observations	398,880	6,001	9,747	16,895	29,032	58,130	61,164	101,387
R-squared	0.102	0.032	0.031	0.044	0.078	0.100	0.114	0.110
Number of team1id	4,923	70	104	188	325	620	777	1,808
Adjusted R-squared	0.0906	0.0177	0.0186	0.0327	0.0668	0.0900	0.103	0.0938

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 2.32. Away Goals with 3G pitches (Both clubs with 3G pitch), with controls and fixed effects

VARIABLES	(1) All Steps Away Goals	(2) Step 1 Away Goals	(3) Step 2 Away Goals	(4) Step 3 Away Goals	(5) Step 4 Away Goals	(6) Step 5 Away Goals	(7) Step 6 Away Goals	(8) Step 7 Away Goals
Home and Away 3G	0.026	0.333**	0.067	-0.108*	0.113	0.017	0.091	-0.261
	(0.038)	(0.152)	(0.075)	(0.059)	(0.069)	(0.092)	(0.092)	(0.224)
Elopredict	-1.627***	-0.445*	-0.768***	-1.132***	-1.029***	-1.523***	-1.510***	-1.856***
	(0.028)	(0.229)	(0.157)	(0.123)	(0.082)	(0.067)	(0.062)	(0.056)
League Position (Home)	0.018***	0.002	0.003	0.001	0.009***	0.015***	0.021***	0.025***
	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
League Position (Away)	-0.043***	-0.014***	-0.014***	-0.016***	-0.022***	-0.033***	-0.044***	-0.056***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Total Goals Scored (Home)	-0.001***	0.000	-0.001*	-0.001	-0.001***	-0.002***	-0.001***	-0.002***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Goal Difference (Home)	-0.009***	-0.005***	-0.004***	-0.006***	-0.006***	-0.005***	-0.006***	-0.007***
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Constant	2.837***	1.648***	1.881***	2.153***	2.172***	2.667***	2.817***	3.022***
	(0.018)	(0.136)	(0.102)	(0.078)	(0.056)	(0.044)	(0.043)	(0.038)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626
R-squared	0.079	0.019	0.023	0.036	0.047	0.074	0.091	0.083
Number of team1id	4,937	70	104	188	325	624	777	1,810
Adjusted R-squared	0.0683	0.00505	0.0110	0.0246	0.0357	0.0637	0.0793	0.0669

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 2.33. Goal Difference with 3G pitches (Both clubs with 3G pitch), with controls and fixed effects

VARIABLES	(1) All Steps Goal Difference	(2) Step 1 Goal Difference	(3) Step 2 Goal Difference	(4) Step 3 Goal Difference	(5) Step 4 Goal Difference	(6) Step 5 Goal Difference	(7) Step 6 Goal Difference	(8) Step 7 Goal Difference
Home and Away 3G	-0.099*	-0.307	-0.010	-0.006	-0.229**	-0.081	-0.063	0.300
	(0.060)	(0.226)	(0.114)	(0.090)	(0.106)	(0.144)	(0.146)	(0.352)
Elopredict	3.603***	1.061***	1.858***	2.394***	2.370***	3.333***	3.499***	4.123***
	(0.044)	(0.340)	(0.238)	(0.186)	(0.126)	(0.104)	(0.097)	(0.089)
League Position (Home)	-0.043***	-0.010*	-0.005	-0.005	-0.017***	-0.029***	-0.042***	-0.049***
	(0.001)	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
League Position (Away)	0.106***	0.038***	0.031***	0.042***	0.065***	0.085***	0.106***	0.141***
	(0.001)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Goal Scored per game (Home)	-0.001***	-0.001	-0.001	-0.001	0.001	0.001	-0.000	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Goal Diff per game (Home)	0.017***	0.008***	0.010***	0.011***	0.011***	0.009***	0.012***	0.013***
	(0.000)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-2.105***	-0.533***	-0.881***	-1.494***	-1.546***	-2.131***	-2.345***	-2.606***
	(0.028)	(0.202)	(0.154)	(0.118)	(0.086)	(0.068)	(0.069)	(0.060)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626
R-squared	0.145	0.046	0.045	0.068	0.105	0.140	0.163	0.155
Number of team1id	4,937	70	104	188	325	624	777	1,810
Adjusted R-squared	0.134	0.0321	0.0335	0.0573	0.0946	0.131	0.152	0.140

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 2.34. Outcome Home Win with 3G pitches (Both clubs with 3G pitch), with controls and fixed effects

VARIABLES	(1) All Steps Outcome Home Win	(2) Step 1 Outcome Home Win	(3) Step 2 Outcome Home Win	(4) Step 3 Outcome Home Win	(5) Step 4 Outcome Home Win	(6) Step 5 Outcome Home Win	(7) Step 6 Outcome Home Win	(8) Step 7 Outcome Home Win
Home and Away 3G	-0.001	0.027	-0.007	0.019	-0.016	0.013	-0.002	0.026
	(0.011)	(0.067)	(0.031)	(0.023)	(0.026)	(0.031)	(0.029)	(0.066)
Elopredict	0.526***	0.308***	0.472***	0.474***	0.462***	0.530***	0.526***	0.519***
	(0.008)	(0.099)	(0.065)	(0.048)	(0.030)	(0.022)	(0.019)	(0.017)
League Position (Home)	-0.006***	0.000	0.004**	0.001	-0.002*	-0.000	-0.004***	-0.002***
	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
League Position (Away)	0.017***	0.009***	0.007***	0.009***	0.012***	0.015***	0.017***	0.022***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Goal Scored per game (Home)	0.008***	-0.006	0.005	0.020	0.018**	-0.006	-0.004	-0.006*
	(0.002)	(0.025)	(0.018)	(0.013)	(0.009)	(0.006)	(0.005)	(0.003)
Goal Diff per game (Home)	0.037***	0.047**	0.065***	0.034***	0.043***	0.058***	0.042***	0.042***
	(0.001)	(0.021)	(0.014)	(0.011)	(0.007)	(0.004)	(0.003)	(0.002)
Constant	0.069***	0.183**	0.082	0.033	0.032	0.015	0.030*	0.020
	(0.006)	(0.072)	(0.052)	(0.038)	(0.026)	(0.018)	(0.017)	(0.013)
Observations	398,880	6,001	9,747	16,895	29,032	58,130	61,164	101,387
R-squared	0.100	0.031	0.034	0.041	0.070	0.094	0.111	0.101
Number of team1id	4,923	70	104	188	325	620	777	1,808
Adjusted R-squared	0.0887	0.0168	0.0217	0.0295	0.0591	0.0837	0.0991	0.0844

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

We also include the regressions where two clubs with a 3G pitch play each other (Tables 2.30-2.36). These have similarly mixed results. There are some significant effects on attendance where it appears to negatively affect attendance at higher levels this may simply be that these clubs are less well supported on average. There is also a positive effect on attendance at Step 5. Advantages for the home club are cancelled out, which is to be expected based on what we've found elsewhere. What perhaps is less expected is that the away club can gain an advantage, or it may be that home advantage is cancelled out, due the pitch effects not being an advantage for the home club. The away club at Step 1 has more chance of winning and scoring more goals if both clubs have a 3G pitch, which indicates that home advantage is effectively taken away if the pitch was providing part of it in the first place.

2.5 Conclusion

We find there are some small positive effects for 3G pitch use increasing both off-pitch success in terms of attendance at specific Steps and pitch types and on-pitch in terms of an increase in the number of goals over a season and likelihood to win a match. These effects though are varied across the non-league structure, fitting with some of the previous literature on demand (in terms of attendance) and performance (in terms of competitive balance and on-pitch performance). Any positive effects are more powerful (and likely to be of more value) in the lower steps of the league structure. Any increase in attendance at Step 7 or 8, for instance, is likely to lead to an increase in revenue, then the value of the pitch to the club both on the pitch and off the pitch as a community asset will also increase, although caution should be exercised as the data at this Step or lower, is clearly not as reliable, especially relating to attendance. These are also Steps with the highest amount of matches due to the number of leagues contained within that part of the structure but also lowest concentration of clubs with 3G pitches so effects may be dispersed, and it may be worth examining individual club performance to greater effect. At the lowest level, what we can't measure is, whether the clubs will be less likely to retain enough of the same players year on year to get used to the pitches. We note the effect of Covid-19 on football attendances (and likely performances) and although this affected clubs financially in an unplanned way and still has lasting effects, the overall number of clubs in existence has not drastically reduced. Therefore, we would conclude that if the effects of 3G pitches are somewhat specific and probably reduced, then the likelihood of a home win for fans, or a competitive match for neutrals is a greater driver of attendance, at higher levels within the non-league structure.

Chapter 3

Community ownership of football clubs at the grassroots level, measuring performance through attendance and on-pitch outcomes

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3.1 Introduction

A significant part of sports economics research has been devoted to understanding the motivations for the ownership of football clubs. While the long life of many clubs, formed in the mid-nineteenth century, implies some degree of sound financial management, the continual financial troubles of the same clubs suggest otherwise. Some of the earliest contributions (Sloane, 1971) considered whether owners might rightfully be considered profit maximisers as per any other industry, or rather utility-maximisers. These motivations for ownership would, naturally, have different implications for the decisions taken by club owners. A particular tension for such clubs is that they have a large number of significant stakeholders, supporters or "fans" of the club, who exert significant influence over the club's decision making without any formal decision-making power. In recent years, fans forming collectives and taking outright ownership of clubs has become increasingly common (with there now being 43 fan-owned clubs in the dataset we use in this chapter) as the tensions between fan stakeholders and club ownership have reached breaking point. Because most clubs throughout football operate at a loss on an annual basis there is an implication that fan ownership, where a wealthy individual or syndicate is not funding club operations, must be detrimental to sporting outcomes.[36] In this chapter we utilise a novel dataset on instances of fan ownership throughout football in England and evaluate the extent to which this is true. While decisions by the fans to take ownership of their clubs are usually motivated by the simple existence of the club, an analysis of such wider implications of such ownership structures will be important for the governing authorities in the game In particular as the UK government intends to create an

[36] https://www.deloitte.com/uk/en/services/financial-advisory/research/annual-review-of-football-finance-europe.html (Accessed 12/9/24) The annual football finance report from Deloitte details the financial situation of some of the most popular teams in Europe.

independent football regulator, such issues have arguably never been more pertinent, and the analysis in this chapter feeds into that context[37].

The Football Supporters Association (FSA) defines 'community ownership' as 'clubs controlled by their members who own at least 50+1% of the voting rights through and open and transparent democratic model that encourages fan participation'.[38] Any profits that are made are also reinvested into the club and it is supposed to be a sustainable business model (The Football Suppporters Association, 2021). Our motivation in pursuing this research was in part that EFL clubs such as Reading and Derby County have in recent years been punished financially and through point deductions where owners have failed to comply with league regulations, led to relegation. [39] These are two of the most recent high-profile cases but there are a number of other examples throughout football and one interest is whether a fan ownership model could be a tangible benefit and thus help with preventing or reducing this non-compliance with rules. Some examples of where ownership has been controversial relating to non-league football and fan ownership directly, have been Manchester United, where fans set up an alternative club 'FC United' after disagreeing with commercial direction of one of the most famous and successful clubs in the world (Torchia, 2016). A further example could be Bury FC, formerly a football league club that after being removed from the EFL in 2019, fans taking over ownership have finally been able to buy back the stadium that historically was owned by the club.[40]

We assess only the model of fan ownership vs non-fan ownership, as there is a definitive current list and the data, we use is recent enough that it is relatively straightforward to research any clubs that may have been 'fan-owned' during the

[37] https://lordslibrary.parliament.uk/research-briefings/lln-2024-0029/
(accessed 16/9/24) Labour committed to an independent football regulator in the King's Speech to examine football ownership.
[38] Football Supporters Association https://thefsa.org.uk/news/community-owned-clubs-directory-launched/ (accessed 7/2/2024). The 50+1 rule means that the fans own at least 50% of the shares of the club, or 50% of the voting rights.
[39] https://www.theguardian.com/football/2021/nov/16/derby-deducted-another-nine-points-for-breaches-of-efl-rules-over-pride-park-sale (accessed 12/9/24) https://www.bbc.co.uk/sport/football/68413946 (accessed 12/9/24)

[40] Football Supporters Association https://thefsa.org.uk/news/the-return-of-bury-fc/ (accessed 7/2/2024)

period studied but no longer are. Other models of ownership are not currently consistently classified by any other organisation. We also cannot measure individual club level decisions across this period but what we can do is compare fan owned clubs to non-fan owned clubs over time and in terms of attendance and on-pitch performance.

There are other versions of this ownership model elsewhere in European Football, that also include the 50+1 rule, with examples of some of the most famous clubs in Europe being ‘fan-owned’, such as most of the professional German clubs (Bauers et al., 2020), and Barcelona & Real Madrid, where elections for club president receive a sizeable amount of media coverage.

We focus on the grassroots level in English non-league football only, as the rules allowing for directly fan-owned clubs in the EFL are restrictive and prevent full ‘fan-ownership’ (The Football Suppporters Association, 2021). There have also been many studies of the EFL or Premier League but thus far, very few involving the English non-league and is one of our contributions to the literature by expanding this into grassroots football. Fan or supporter-owned clubs though are currently not the norm in England, although their numbers have increased slightly, particularly between 2010-2015 (see figure 9). There are currently 43 clubs in our database over the period we cover. Some of these have had some relative success, at least when compared to clubs with a similar fan base, financial resources and results on the football pitch. The most successful examples in terms of promotions and league wins for fan-owned clubs, are clubs such as, AFC Wimbledon and Exeter City (top of League One in the EFL as we type this). These clubs have established themselves as strong EFL clubs after rebuilding from the grassroots level when reforming as new fan-owned clubs. We cannot access the financial records of each club but can get data on the matches and attendances which gives us a good measure of the financial success and performance at the grassroots level. Most football Clubs rely on financially well-resourced, benevolent owners or enough fans attending to maintain financial stability (UK Companies House records are very limited for what are essentially quite small local businesses). There are few academic studies of English non-league football and one of our contributions to the growing football economics literature is to provide this study, in addition to Chapter Two. One reason is likely to be that until recently, data was hard to obtain, another is the focus on elite level football at the Premier League or European continental level of competition as has many years of detail rich data and the added factor of attracting greater attention as the more successful clubs are internationally renowned and more likely to create research impact.

Football fans are different to fans of other leisure pursuits, such as pop music or cinema or even a particular brand of clothing, in that brand loyalty for many is something that occurs early on in life and remains lifelong, giving a somewhat captive audience at least for a core of the regular club support. With music for instance, it is rare that someone is a fan of only one, or even two bands, whereas the fan that regularly attends matches is likely to be exclusive, or possibly has a 'second' elite or grassroots favourite club. This is not just about brand loyalty though, it is often about a sense of place, belonging, is usually something one decides at a younger age but it is not always a worldwide phenomenon, with fans from countries where their own local club system is less successful often supporting historically internationally renowned clubs such as Manchester United or Barcelona. Fans of non-league clubs, on the other hand have often been known to have an elite club as their 'second club' or vice-versa, going to visit the non-league club when their home club is playing away from home (Watkins and Cox, 2020).

In terms of fan-ownership specifically, in most instances, fans have taken ownership because the club has faced bankruptcy or is already in 'administration' (where football-related debts such as wages owed to players and staff, and transfer fees owed to other clubs to be paid first). Local fans have sometimes grouped together organically (usually through various local networks) to either buy at least 50% of the shares relating to the club ownership or have started at less than 50%, gradually building up their share over time. In other instances, they have set up a separate company to buy the club, with each fan holding an equal share. There is an element of desperation about this situation, in that usually other avenues have been exhausted.

If the club has had a previous owner that wanted to, in the short term, maximise profits from the clubs assets (without regard to the effect on the pitch or longer term benefits to the club) or the club has gone into administration, then the main assets such as stadiums or training facilities may have been sold and it can take years (and a significant amount of financial support) to buy them back. Obtaining consistent information on assets of all fan-owned clubs or all non-fan-owned clubs in order to compare each type, would currently be very difficult for a project this size.

Apart from contributing to the rich football economic literature, our work is situated within the competitive balance and outcome uncertainty literature that provides some of the best explanations for why fans attend matches. One of the earliest discussions of competitive balance and viewing football clubs as firms sets out that football clubs differ from normal business models (Sloane, 1971). In the leagues we study, promotion and relegation are possible although there are restrictions for smaller clubs that are successful. Significant financial outlay may be necessary to compete at higher levels (such as improving minimum stadium size or facilities but also including higher wages to players, particularly at the national league level) and occasionally the highest or higher placed clubs at the end of a season, fail to meet the next division or Step's requirements. One study of promotion and relegation in English football found that the effect of promotion and relegation is ambiguous but that it has a positive effect on player wages and attendance (Noll, 2002), Buzzachi et al, though find that open leagues are less balanced (Buzzacchi et al., 2003) but in a different study found that the issue is around income sharing across the league, which is reduced in competitive leagues, whilst promotion and relegation can increase incentives (Szymanski et al., 2010). A study of European football revenue and competitiveness across the 5 top performing leagues in Europe, led to the conclusion that income distribution needs to be altered to allow for clubs with less financial capacity to compete more regularly with the top performing and most profitable clubs (Ozaydin and Donduran, 2019). In non-league football, small differences in revenue and income generation could lead to large imbalances, especially where clubs have been reformed from bankrupt clubs that are then utilising the previous defunct club facilities and presumed larger local resources.

In terms of attendance demand specifically, Forrest and Simmons point out that attending a football match is a time intensive (and also potentially expensive even at non-league level) commitment, that fans do exhibit behaviours that respond to poor or good performances but that uncertainty of outcome is not particularly relevant (Forrest and Simmons, 2006). Attendances in that study though focused on those just outside of the top division professional division in England, and so attendances were still based on very well-known clubs that were much better attended than English non-league matches. Reade finds that loyalty, quality and how nearby the visiting club is can affect attendance but that fans aren't that bothered by how balanced a match might be (Reade, 2021)

Earlier studies into attendance demand, such as by Neale (Neale, 1964) established league position and competitive balance as being important factors in attendance demand. Hart, et al (Hart et al., 1975) found that club quality and geography were important. Other studies such as by Dobson and Goddard, suggest that when studied over a long period, attendance is driven by results, price and goals scored but over the longer period, unemployment rate may be a factor (Dobson and Goddard, 1996). Having price date (on ticket prices) allows for a study to examine price elasticities and inelastic demand, as fans tend to stick to a club regardless (García and Rodríguez, 2002), unfortunately this is only something we can capture in an error term as we do not have price effects for our data (and even if we could, it would be hard to capture for such a wide period of time with so many matches).

A study on Peruvian football clubs found that market size, distance between clubs and form were effects on attendance but rivalry didn't make a great deal of difference to demand (Buraimo et al., 2018).

Earlier research into club ownership and profit maximisation found that clubs are generally inefficient and until the Premier League era, a number of clubs faced financial crises (Szymanski and Smith, 1997). Football fans though can bear the burden of this inefficiency as clubs are often laden with debt that owners take on using the club as the asset but then expecting the fans to continue to pay more to watch their club (Kennedy and Kennedy, 2012).

A paper on the League of Ireland, provides some useful similarities with Step 1 & 2 English non-league attendances and dynamics, with a lack of star players and stadiums often not filled to capacity (but similar average attendances), the clubs at League of Ireland level also retain very few players on full-time contracts as most are part-time and some clubs are 'fan-owned', the suggested solution to competitive imbalance in this league was to reduce the size and thus increase match uncertainty outcome (Reilly, 2015).

Other than those falling into the category of 'community owned' clubs, there are those who have foreign investors (usually found more in the professional leagues) or local based owners (Rohde and Breuer, 2018) with foreign investors found to be inefficient at maximising either financial or sporting performance, both in England and France, although this was at the elite level.

In terms of helping to define, 'community owned' clubs, specifically, this means considering the active participation of members, shareholders or residents having a direct input into outcomes. There are clubs that call themselves ‘community clubs’ that do work closely with their local communities but this takes many forms and is often ‘indirect’, in that the community may be consulted but the club owners have the ultimate say. Community ownership can improve relationships between the community and the entity being ‘owned’ (Warren and McFadyen, 2010) and attitudes towards that entity.

Reference was made earlier comparing the demand for football to non-sporting entertainments and why football clubs are different. It is worth noting though that there are similarities with football and other sports, in terms of both ownership models and the demand. Wilson and Plumley found that changes to Rugby club ownership after professionalism seems to have made leagues more competitive reducing the imbalance (Wilson and Plumley, 2017) whereas Vrooman found that with American Football, the franchising system restricts movement of players (Vrooman, 2000, Vrooman, 2011). With basketball in the US, Ulas finds that similar indicators of club value are found such as revenue, the rank of league the club plays in, the ability of players and location but that on field poor performance also affected value (Ulas, 2021). There are also similarities to rugby with home win likelihood being a strong determinant of attendance in the short term (Hogan et al., 2017) but with short term uncertainty having little effect, only to be a factor medium term if clubs were likely to reach knock out levels. When examining the re-location of MLS Soccer clubs, it was found that locating them near to existing American Football or Basketball clubs was positive in terms of generating increased game attendance, having a nearby NHL (Hockey) or MLB (Baseball) club was detrimental, demonstrating some issues in terms of competing interests for sports(Semmelroth et al., 2022).

Although the approach of this paper is from an economics perspective, we also need to examine some of the qualitative research conducted into fan-loyalty, especially as there is research covering the economic setting we are interested in, that of non-league

English football. There is research into why fans share their loyalty between a more elite level club and a local non-league club, it is of course easier to watch an elite club on television but a local club can lead to greater connectedness to an area and a sense of belonging (Watkins and Cox, 2020). Other aspects of non-league football can also be attractive, especially after years of following an elite club, with less regulation in terms of the live-viewing experience (able to drink alcohol whilst watching the match, fans mingling with opposition fans more easily and less-partisan expressions) and even the slightly more chaotic and changing experience year on year as clubs financially struggle but still have relative success (Williams and Caulfield, 2020).

Any discussion of issues at stake with ‘fan ownership’ or participation in board decision making processes takes us into some area of management theory and not just economics. Some of these studies have focused on which type of fans have greater involvement in decision making, or which types of structures actually give fans greater involvement (Uhrich, 2021). The main focus has generally been on the German Bundesliga structure where the majority of clubs are fan owned with there being some positives for fans if they accept management decisions that they have an input into and where there is a culture of openness (Uhrich, 2021). Voluntary structures though need clear lines of management decision making and with ambiguous structures or responsibilities this can hamper both development of permanent staff and essentially hold back the organisation compared to other more professional setups (Thiel and Mayer, 2009). The contrast to this though is the commitment from volunteers is often greater in more rural areas and with less professional structures but also stronger identification with the club itself (Schlesinger and Nagel, 2013). A case study of Exeter City suggests that whilst there may be benefits to a mutual ownership model involving the fans, it can also lead to additional bureaucracy levels, due to additional members to be consulted on decisions (Ward et al., 2013). A further issue with the German model applies more to elite level competitiveness, in that to compete with the highest ranked clubs in Europe at Champions League level or in the top divisions of the top leagues in Europe usually requires additional significant investment, which is more difficult to achieve with fan-owned models (Ward and Hines, 2017).

We have highlighted literature that focuses on the competitive balance and attendance demand in football, which is clearly relevant to establishing why fans attend matches at any level of the sport. However, some of the issues relating to fan-ownership, participation and locality are teased out. Even in German elite football, it is clear that apart from one or two clubs, fan-ownership models may be restrictive for taking clubs to whatever the next level is, if the majority of competitors is not fan-owned.

3.2 Data

Our data consists of the 412, 922 matches that take place in the seasons between 2011/12-2022/3, as also used in Chapter Two, this allows us to focus on the non-league structure where the majority of fan-owned clubs exist in England. We have attendance data for 187,022 of these matches (matches taking place from Step 7 and below are often played in front of no fans or no recorded fans). As Table 1 in the thesis introduction lays out, the structure of non-league football in England takes place over a number of Steps. With these steps having different numbers of leagues within their regional structure (usually a county league, with wide variances in the size of county – some are combined and others overlapping into more formal UK county structures). An important feature of this 'Step' structure is that clubs can be promoted and relegated and it is possible to move through the structure from one Step to another. There are however some financial restrictions and rule changes to be met at different Steps.[41] Some of these have been prohibitive financially and stopped promotion based on performance.[42]

[41] https://sgsa.org.uk/regulatory-support/legislation/alcohol-at-football-grounds/ (accessed 15/9/24) importantly for instance, alcohol is not available 'pitch side' at the top non-league, Step 1 National League, making for an important revenue difference on promotion.
[42] https://www.bbc.co.uk/sport/football/articles/c3g5pg2e3x5o Gateshead were in 2024, not promoted to League 2, from Step 1 as their stadium did not meet the EFL requirements and similar restrictions are in place across different Steps.

Table 3.1. Community Owned Clubs Summary Statistics

Variable	Obs	Mean	Std.dev	Min	Max
Match with Fan Owned Club	414,086	0.015	0.123	0	1
Year Fan Owned	8,298	2011.902	5.004	2001	2021
Home Goals	414,086	2.124	1.878	0	28
Away Goals	414,086	1.837	1.687	0	30
Outcome Home Win	414,086	0.453	0.498	0	1
Outcome Draw	414,086	0.173	0.378	0	1
Outcome Away Win	414,086	0.374	0.484	0	1
Eloprediction	414,086	0.500	0.125	0.048	0.952
Home Points (at time of match)	414,086	21.207	17.625	0	119
Away Points (at time of match)	414,086	21.337	17.810	0	113
Home Wins (at time of match)	414,086	6.201	5.396	0	39
Away Wins (at time of match)	414,086	6.245	5.458	0	37
Games Played (at time of match)	414,086	14.988	10.352	0	53
Total Goals Scored (Home)	414,086	29.305	22.295	0	167
Total Goals Conceded	414,086	29.453	22.545	0	190
Home Goal diff	414,086	0.042	22.006	-279	148
Away Goal Diff	414,086	0.322	22.061	-315	163
Home league Position	414,086	9.338	5.479	1	36
Arway League Position	414,086	9.302	5.474	1	36
Attendance	187,492	232.995	521.348	0	16511
Log Attendance	187,148	4.693	1.071	0	9.712
Step	408,481	6.318	1.843	1	13
Home Goal Difference in match	398,880	0.004	1.527	-18.25	18
Home Goals Scored per match	398,880	2.005	0.905	0	18
Game at Weekend	414,086	0.766	0.423	0	1
Goal difference in game between teams	414,086	0.287	2.749	-29	28

In total, we have 43 clubs that are 'fan-owned'. Over the 2011-2023 period, this gives us 6373) matches out of the 412,922 in total in our database (1.5% of the overall sample. Although Table 3.1. shows clubs with the 'year fan owned', this is not the season but the year, whereas our variable for indicating fan-ownership is recorded at the match level, indicating the club is fan owned only for that match at that point of fan ownership and until the end of the dataset or ceasing if the club was sold to new owners. Not all of the clubs are now currently fan-owned as some of them later reverted to other forms of ownership during the period covered (or were promoted out of the non-league structure into the EFL) but the data contains any clubs that were fan-owned over the period at the point the match takes place, in the national league structure (we also show if the club was later sold to a different owner). We can also see the large variances in attendance, demonstrating why we use Log Attendance and that the average 'Step' for all clubs is between 6 and 7, which is simply where the Step with the most leagues is to be found (Step 7).

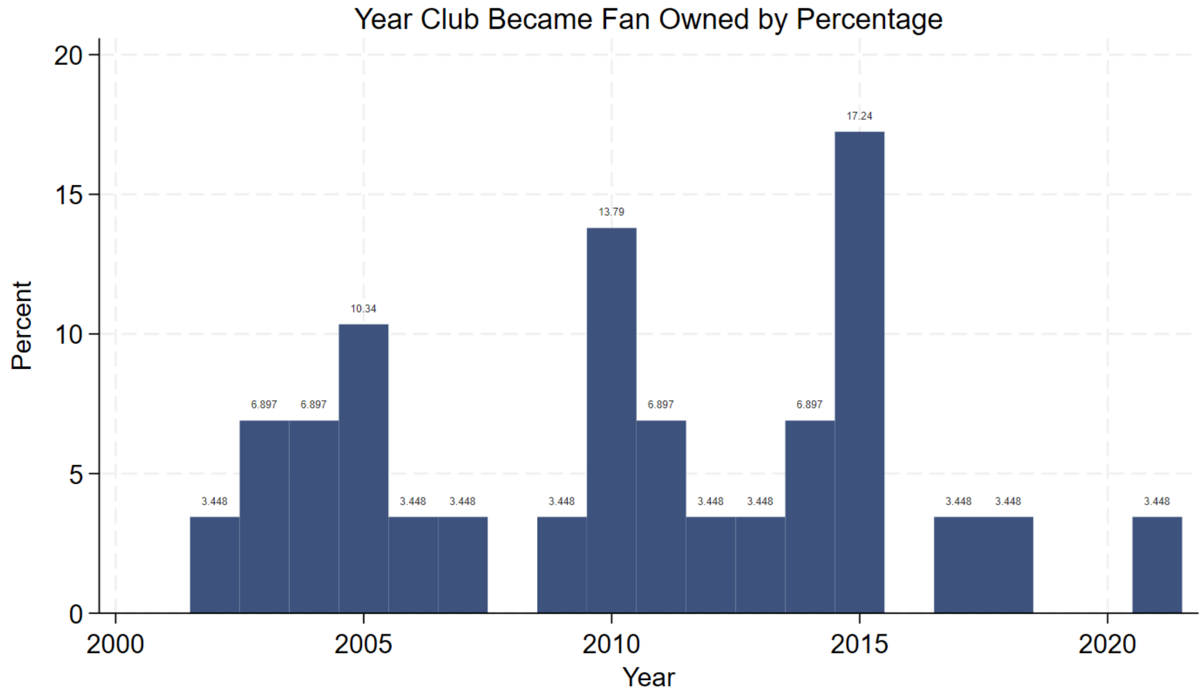

Figure 9. Year Club became Fan owned by percentage (all Steps).

We can see in figure 9 (above) that there are some peak periods for when clubs have become fan owned (2005, 2010 and 2015), the greatest concentration being from 2010-2015, showing that whilst some clubs were fan-owned prior to our data collection in 2011, a significant number become fan-owned at different points during the 2011-2023 period. Unlike with 3G pitches, there being a policy intervention making it easier for clubs to bid for pitches (as mentioned in Chapter Two), there is no particular policy event that we are aware of that encourages clubs to become fan owned.

Table 3.2. Matches containing Fan Owned clubs by Step (Seasons 2011-2023)

Step	Observations (matches)	Precentage of Fan owned matches	Std. dev.
Step 1	6,145	0.080	0.272
Step 2	10,015	0.076	0.265
Step 3	17,358	0.105	0.307
Step 4	29,870	0.037	0.189
Steep 5	59,855	0.023	0.151
Step 6	63,142	0.007	0.085
Step 7	105,626	0.002	0.045
Step 8	93,782	0.001	0.025
Step 9	17,311	0	0
Step 10	1,953	0	0
Step 11	1,923	0	0
Step 12	825	0	0
Step 13	676	0	0
No Step	5,605	0.010	0.099

In Table 3.2. we demonstrate the split of matches by Step, where fan owned clubs take part. What becomes clear is that whilst the largest concentrations of non-league matches take place between Steps 6 and 8, the number of clubs that are fan-owned, taking part in these matches at that level is very few. In the top 3 Steps though, we can see that at various points across the data, fan owned clubs are of a significant enough concentration (between 7-10%) that there is more than one or two clubs per league. There are no fan-owned clubs recorded after Step 8 and this is to be expected, as after Step 7, additional steps are regional 'add-ons' in that the number of Steps varies from Region-to-Region and County-to-County, with areas with higher concentration of clubs having more Steps. Table 3.2. makes clear that the larger number of matches with a fan-owned club takes place at Step 3 or higher.

Table 3.3. Comparison Summary Statistics of Fan-owned and clubs that are not Fan Owned

Non Fan Owned Clubs

Attendance	Log Attendance	Total Goals Scored (at time match takes place)	Total Goal Difference (at time match takes place)	Average League Position (at time match takes place)	Average no. of Home Goals scored per game	Goal Difference/game
214.779	4.650	29.252	-0.038	9.324	2.009	-0.0010

Actual no. of goals scored in a match (home)	Actual no. of goals scored in a match (away)	Average Step	Average Goal Difference (at point match takes place)	Home Win	Away Win	Draw
2.127	1.845	6.358	0.282	0.452	0.375	0.173

Fan Owned Clubs

Attendance	Log Attendance	Total Goals Scored (at time match takes place)	Total Goal Difference (at time match takes place)	Average League Position (at time match takes place)	Average no. of Home Goals scored per game	Goal Difference/game
788.809	6.022	32.705	5.170	10.210	1.750	0.2541

Actual no. of goals scored in a match (home)	Actual no. of goals scored in a match (away)	Average Step	Average Goal Difference (at point match takes place)	Home Win	Away Win	Draw
1.914	1.327	3.740	0.587	0.497	0.294	0.209

In Table 3.3., we can see the comparison of the two types of clubs, clubs that are not fan-owned and those that are. We can see that fan-owned clubs overall, have higher attendances but then they are also more likely to be found on average somewhere between Steps 3-4. Fan-owned clubs do tend to have scored more goals at the point the match takes place and have greater average goal difference but conversely can be found at slightly lower league positions. They don't tend to score as many goals per game as clubs that are not fan owned but do tend to prevent more goals (Fan-owed clubs have lower average away goals per game). They do tend to win at home more but also are slightly more likely to draw.

Table 3.4. During Covid-19 restrictions (2020-21) and after (2021-22).

Season 2020/21 Affected by Covid Restrictions

Variable	Obs	Mean	Std. dev.	Min	Max
Step 1					
Match Has Fan Owned Team	462	0.045	0.209	0	1
Log Attendance	47	6.802	0.482	5.820	8.342
Attendance	47	1027.596	674.874	337	4197
Step 2					
Match Has Fan Owned Team	330	0.124	0.330	0	1
Log Attendance	26	6.117	0.581	4.575	6.983
Attendance	26	519.885	246.355	97	1078
Step 3					
Match Has Fan Owned Team	335	0.107	0.310	0	1
Log Attendance	333	5.806	0.411	4.234	6.397
Attendance	333	359.345	135.738	69	600
Step 4					
Match Has Fan Owned Team	495	0.044	0.206	0	1
Log Attendance	483	5.308	0.473	3.497	5.991
Attendance	483	224.362	100.042	33	400
Step 5					
Match Has Fan Owned Team	1,548	0.019	0.138	0	1
Log Attendance	1,293	4.725	0.509	3.178	5.768
Attendance	1,293	128.148	66.86	24	320
Step 6					
Match Has Fan Owned Team	1,873	0.009	0.092	0	1
Log Attendance	1,569	4.452	0.535	2.48	5.79
Attendance	1,569	98.685	54.734	12	326
Step 7					
Match Has Fan Owned Team	3,615	0.003	0.058	0	1
Log Attendance	178	3.944	0.513	2.303	5.106
Attendance	178	58.258	28.092	10	165

2021-22 (Post-Covid, Full season where fans were allowed)

Variable	Obs	Mean	Std. dev.	Min	Max
Step 1					
Match Has Fan Owned Team	818	0.027	0.162	0	1
Log Attendance	810	7.790	0.711	5.989	9.712
Attendance	810	3141.184	2464.041	399	16511
Step 2					
Match Has Fan Owned Team	1,495	0.151	0.358	0	1
Log Attendance	1,368	6.780	0.602	4.963	8.414
Attendance	1,368	1054.345	677.218	143	4512
Step 3					
Match Has Fan Owned Team	2,867	0.118	0.322	0	1
Log Attendance	2,857	5.964	0.615	4.007	7.892
Attendance	2,857	476.837	361.300	55	2676
Step 4					
Match Has Fan Owned Team	4,610	0.051	0.220	0	1
Log Attendance	4,551	5.443	0.679	3.258	8.414
Attendance	4,551	297.903	284.056	26	4512
Step 5					
Match Has Fan Owned Team	9,294	0.023	0.150	0	1
Log Attendance	8,288	4.769	0.678	2.485	8.460
Attendance	8,288	155.761	208.109	12	4720
Step 6					
Match Has Fan Owned Team	9,685	0.0144	0.1189	0	1
Log Attendance	8,584	4.3456	0.6993	0.693	7.781
Attendance	8,584	102.968	127.594	2.000	2395
Step 7					
Match Has Fan Owned Team	16,281	0.002	0.047	0	1
Log Attendance	1,574	3.894	0.580	1.386	6.295
Attendance	1,574	58.323	40.376	4	542

In Table 3.4., we detail the effect of Covid-19 on the latter period of our data set. Firstly (not shown) is the season 2019-20 that was curtailed in March with the onset of Covid-19 in March 2020, following in late-March, the effective national 'lockdown' announced by the UK government, stopping football from taking place. We show the during and after-effects (after essentially returns to normal levels of attendance) of the periods when Covid affected attendance and after, making it easier to understand the likely effect on club finances when they largely rely at this level on fans paying to attend and watch games (plus the revenue from food and beverages sales at the ground). We can see that hardly any matches in the top two Steps had fans allowed to attend and even if they were attendances were not only 'capped' to prevent enforced 'closeness' at the stadiums, even if they were allowed to attend the averages were down to only 20% of those at normal levels. Even outside the top Steps where stadia may be more likely to be closer to capacity at particular games, outside of that we can see the effect on clubs at these levels where the average attendances are still significantly reduced. This also effectively means that within our dataset we have two seasons that are ‘incomplete’ in that final league positions were either calculated by the league or were fixed at the point the league ended, even if not finished.

3.3. Methodology

As with Chapter Two, our unit level of analysis is at the match level with club i and away club j at time t.

We model the effect of fan-ownership on log attendance, goals (home and away) and measurements of outcomes in football matches, we do this with data on fans attending matches over the seasons 2011/12 through to 2022/23 across each step of the English non-league football structure where data is available. Our *FanOwnClub* variable is a binary variable that is *FanOwnClub* = 1 if a club is fan owned at the time the match takes place.

We employ a standard difference in differences approach:

$$LogAtt_{Y_{ijt}} = \alpha + \beta 1_{FanOwnClub_{ijt}} + \beta 2_{Elo_{ijt}} + \beta 2_{Elo^2{}_{ijt}} + \beta 3_{LgPosHome_{ijt}} \\ + \beta 4_{LgPosAway_{ijt}} + \beta 5_{GoalsHome_{ijt}} + \beta 6_{GDHome_{ijt}} + _{\xi it} + _{eit} \quad (1)$$

Our main dependent variables are in two parts, the first relating to attendance and the second part a number of on-pitch performance variables. We use log-attendance as there are wide variances in attendance data, with larger ex-EFL clubs like Notts County regularly getting many thousands every match, whereas at the other end of the structure, matches at Step 7 or below are attended often only by a handful of people or sometimes zero recorded fans. [43] We use attendance as this is a strong indicator of the main financial income for a club at this level as there is minimal sponsorship, prize money or transfer revenue and most income is linked to attendance, either through ticket sales or refreshment purchases at the ground itself (Cox, 2012), (Wallrafen et al., 2019).

[43] https://www.transfermarkt.co.uk/notts-county/besucherzahlenentwicklung/verein/1045 (accessed 16/9/24) This shows the average attendances for Notts County when in the National League between 2019/20 season-2022/23 season that their average attendance varied between 5,209-8204 (with a 'Covid' Season in between).

For our on-pitch measures of performance, we use dependent variables of Home goals, Away goals, goal difference and the outcome of the match (Home win, Draw, or Away win). These give us a variety of different performance measures to test against. These are also useful proxies for overall club performance, each of which may be affected by the club being fan-owned.

Other independent variables consist of Elo ratings (a ranking rating based on club historical performance data, acting as a proxy for club strength), and depending on the dependent variable, also goals scored divided by games played and goal difference divided by games played (goals per game and goal difference per game). Additionally, we have a variable indicating which step the match takes place at, and we use this to break the matches up into the various 'Steps' for each regression. We also use season, club fixed effects and for the day of the week the match takes place on. This last variable, then controls for if there are postponements (most matches take place on Saturdays and usually at 3pm) such as for poor weather conditions

Our methodology is very similar to Chapter Two, except that we do not have three different categories of 3G pitch data, instead only one category of what constitutes fan ownership, which is denoted by FanOwnClub in the equation above. This means there are 7 regression Tables in total, using first the dependent variable of LogAtt (Log Attendance), our attendance measure, and then the 6 on-pitch measures of Outcome Home Win (HG), Outcome Away Win (AG), Draw (D), Home Goals (HG), Away Goals (AG) Goal Difference (GD), where LogAtt is replaced in (1) by one of these options. In this case the equation alters to include different control variables where we use Outcome Away Win, Draw, Away Goals and Goal difference as the dependent variable, we then also exchange Home Goals (per game) and Home Goal Difference (per game) to replace with Total Goals scored and Total Goal difference as we are not looking at home performance or what determines attendance but factors that might influence Away or neutral outcomes rather than variables that would impact on home performance. One particular issue with the data on fan-owned clubs is that whilst there are enough to produce this study across the Steps, outside of the top two Steps, once leagues split into four or eight leagues, it is much rarer for a fan-owned club to play each other so we cannot accurately test this across the data. This was not a problem encountered in Chapter Two as for 3G clubs there are up to 270 clubs with one form of 3G pitch.

Each regression on the main dependent variables is carried out at the Step level, with season, weekday (weekend) and home club level fixed effects, which are shown in the equation as ξit. Our error term *eit* captures any unobserved factors not already accounted for within the control variables.

We do not repeat the Outcome Uncertainty test in Chapter Two, as apart from the indicator variables for 3G or Fan Owned Club, the dataset is the same and includes the same control variables.

We acknowledge there are some difficulties with the approach of using attendance and on-pitch performance as proxies for financial status or on-pitch quality and we accept that success of clubs could also be attributed to things like legacy resources and facilities of a club. For instance, if a fan owned club is one re-formed from a previous historical entity, then the new club may be able to rent or loan back the facilities owned by the previous club, giving enough similarity to the previous version of the club for fans to continue supporting the newer version.

3.4. Results

Our results are presented using the main dependent variables of Log Attendance, Home Goals, Away Goals, Goal difference (Goal difference between home and away club as a result of the score of that match, not goal difference in the league table at that point in the season), and then outcomes of Home Win, Draw or Away win. These are contained in Tables 3.5-.3.11.

Table 3.5. Log Attendance with Fan Owned Clubs plus controls with Uncertainty of Outcome test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All Steps	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6
VARIABLES	Log Attendance	Log Attendance	Log Attendance	Log Attendance	Log Attendance	Log Attendance	Log Attendance
Fan Owned Match	-0.034**	-0.479***	0.180***	0.104***	0.051	0.277***	-0.019
	(0.016)	(0.055)	(0.040)	(0.031)	(0.036)	(0.038)	(0.105)
Elo Prediction	-0.301***	-2.101***	-1.278***	-1.908***	-1.097***	-0.957***	-0.420***
	(0.047)	(0.398)	(0.252)	(0.173)	(0.099)	(0.085)	(0.074)
Elo Prediction^2	0.327***	2.153***	1.115***	1.651***	0.993***	0.752***	0.261***
	(0.046)	(0.394)	(0.252)	(0.172)	(0.098)	(0.083)	(0.073)
Goals Scored (Home)	-0.005***	-0.003***	-0.002***	-0.003***	-0.003***	-0.005***	-0.004***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Goals Scored (Away)	0.005***	0.004***	0.004***	0.005***	0.005***	0.005***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Goal Difference (Home)	0.004***	0.005***	0.006***	0.006***	0.005***	0.005***	0.005***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
League Position (Home)	-0.005***	-0.013***	-0.011***	-0.010***	-0.009***	-0.011***	-0.009***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Constant	4.726***	7.984***	6.735***	6.243***	5.277***	4.783***	4.326***
	(0.014)	(0.105)	(0.068)	(0.047)	(0.028)	(0.025)	(0.022)
Observations	187,148	5,722	9,584	17,338	29,779	56,355	54,634
R-squared	0.156	0.261	0.191	0.177	0.215	0.159	0.160
Number of team1id	1,566	70	104	188	325	622	757
Adjusted R-squared	0.149	0.249	0.181	0.167	0.206	0.149	0.148

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and weekday

Taking Log attendance first (Table 3.5.), it appears that having a fan-owned club may be a popular differential, in terms of getting fans to attend matches in the mid-range of Steps in non-league football. Steps 7 and 8 are removed because not enough clubs play each other that are fan owned and recorded attendance data (match results are recorded though, as seen in the other Tables). It also appears that fan owned clubs are of less value to increasing attendance at the top and bottom end of non-League football. We would expect that as clubs become successful, they become better known, and in some cases better managed. This then is likely to be part of what reflects the positive effects on Log Attendance across Steps 5 to 2. The Uncertainty of Outcome variables of Elo and Elo^2 are significant throughout which means we can't rule out that expected home win and outcome uncertainty are also driving attendance. That said, a fan-owned club appears to be likely to struggle in terms of attendance at Step 1 with potentially an almost 50% reduction in attendance but for many cases, this is when compared to clubs that are relegated from the EFL Two or clubs that have been at Step 1 for a few seasons and have worked out how to push for promotion. At Step 5 there is a 30% increase in attendance for clubs that are fan-owned, with between 10-17% increases at Steps 2 and 3. It may then be an incentive for fans to take ownership when a club has performed poorly over time and if the longer term aim is to be a EFL club, to then attract enough attention to have the sort of owner that will finance this. A potential financial benefit of this sort of increase could be hugely beneficial to a non-league club.

That this average attendance figure for fan-owned clubs, dramatically drops in Step 1 is likely to be down to the comparison with other clubs in this division, as our dataset contains clubs like Notts County, Wrexham, Stockport, for all of whom there are large supporter bases and clubs that have been in the professional leagues. Wrexham were also fan owned until 2020 but the unusual circumstances of their transfer of ownership from being fan-owned to being one of the better-known clubs in the world, as a result of US film-actors purchasing the club, appears to have altered their attendance to the effect of doubling attendance post-Covid after they were taken over.[44] Outside of Step 1 though, the small or medium effects on attendances that we are recording are of real value to the financial fortunes of clubs that otherwise might struggle to survive, this would be particularly so for a fan-owned club, where they would not be able to fall back on an owner providing loans or servicing debts if average attendances were lower than expected.

[44] https://www.transfermarkt.co.uk/afc-wrexham/besucherzahlenentwicklung/verein/1112 (accessed 16/9/2015) Wrexham ceased to be fan owned in early 2021, after which, when the 2021 season started their attendances increase at their highest of just over 5000 but an average below that, to over 8600 in the 2021/22 season.

Table 3.6. Home goals with Fan Owned Clubs plus controls

VARIABLES	(1) All Steps Home Goals	(2) Step 1 Home Goals	(3) Step 2 Home Goals	(4) Step 3 Home Goals	(5) Step 4 Home Goals	(6) Step 5 Home Goals	(7) Step 6 Home Goals	(8) Step 7 Home Goals
Fan Owned Match	0.045	-0.715***	-0.030	0.032	-0.169	-0.067	-0.224	0.330
	(0.060)	(0.201)	(0.152)	(0.121)	(0.147)	(0.146)	(0.431)	(0.242)
Elopredict	2.001***	0.654**	1.164***	1.280***	1.369***	1.754***	1.938***	2.199***
	(0.032)	(0.256)	(0.176)	(0.134)	(0.092)	(0.074)	(0.070)	(0.065)
League Position (Home)	-0.016***	-0.007	0.004	0.001	-0.004	0.001	-0.008***	-0.010***
	(0.001)	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
League Position (Away)	0.065***	0.024***	0.017***	0.027***	0.043***	0.054***	0.064***	0.089***
	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Goal Scored per game (Home)	0.136***	-0.064	0.059	0.034	0.121***	0.054***	0.087***	0.048***
	(0.006)	(0.064)	(0.047)	(0.035)	(0.027)	(0.018)	(0.017)	(0.013)
Goal Diff per game (Home)	0.092***	0.065	0.100***	0.092***	0.069***	0.134***	0.102***	0.107***
	(0.004)	(0.054)	(0.039)	(0.029)	(0.021)	(0.013)	(0.012)	(0.009)
Constant	0.349***	1.233***	0.752***	0.501***	0.346***	0.241***	0.147**	0.137***
	(0.024)	(0.188)	(0.140)	(0.105)	(0.079)	(0.060)	(0.060)	(0.051)
Observations	398,880	6,001	9,747	16,895	29,032	58,130	61,164	101,387
R-squared	0.102	0.034	0.031	0.044	0.078	0.100	0.114	0.110
Number of team1id	4,923	70	104	188	325	620	777	1,808
Adjusted R-squared	0.0903	0.0198	0.0185	0.0325	0.0668	0.0900	0.103	0.0938

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 3.7. Away Goals with Fan Owned Clubs plus controls

VARIABLES	(1) All Steps Away Goals	(2) Step 1 Away Goals	(3) Step 2 Away Goals	(4) Step 3 Away Goals	(5) Step 4 Away Goals	(6) Step 5 Away Goals	(7) Step 6 Away Goals	(8) Step 7 Away Goals
Fan Owned Match	-0.078	0.040	-0.099	-0.181*	0.268**	-0.013	-0.245	0.342
	(0.053)	(0.176)	(0.137)	(0.109)	(0.133)	(0.131)	(0.381)	(0.215)
Elopredict	-1.628***	-0.460**	-0.759***	-1.131***	-1.025***	-1.524***	-1.510***	-1.857***
	(0.028)	(0.229)	(0.158)	(0.123)	(0.082)	(0.067)	(0.062)	(0.056)
League Position (Home)	0.018***	0.002	0.003	0.001	0.009***	0.015***	0.021***	0.025***
	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
League Position (Away)	-0.043***	-0.014***	-0.015***	-0.016***	-0.022***	-0.033***	-0.044***	-0.056***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Total Goals Scored (Home)	-0.001***	-0.000	-0.001*	-0.001	-0.002***	-0.002***	-0.001***	-0.002***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Goal Difference (Home)	-0.009***	-0.005***	-0.004***	-0.006***	-0.006***	-0.005***	-0.006***	-0.007***
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Constant	2.839***	1.657***	1.886***	2.162***	2.168***	2.668***	2.819***	3.022***
	(0.018)	(0.137)	(0.102)	(0.078)	(0.056)	(0.044)	(0.044)	(0.038)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626
R-squared	0.079	0.018	0.023	0.036	0.047	0.074	0.091	0.083
Number of team1id	4,937	70	104	188	325	624	777	1,810
Adjusted R-squared	0.0683	0.00427	0.0110	0.0245	0.0357	0.0637	0.0793	0.0669

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 3.8. Goal difference between home and away club (at end of each match) with Fan Owned Clubs plus controls

VARIABLES	(1) All Steps Goal Difference	(2) Step 1 Goal Difference	(3) Step 2 Goal Difference	(4) Step 3 Goal Difference	(5) Step 4 Goal Difference	(6) Step 5 Goal Difference	(7) Step 6 Goal Difference	(8) Step 7 Goal Difference
Fan Owned Match	0.110	-0.758***	0.047	0.223	-0.445**	-0.121	0.097	-0.068
	(0.083)	(0.260)	(0.206)	(0.166)	(0.204)	(0.204)	(0.602)	(0.338)
Elopredict	3.603***	1.071***	1.853***	2.394***	2.363***	3.334***	3.499***	4.123***
	(0.044)	(0.340)	(0.239)	(0.186)	(0.126)	(0.104)	(0.097)	(0.089)
League Position (Home)	-0.043***	-0.010*	-0.005	-0.005	-0.017***	-0.029***	-0.042***	-0.049***
	(0.001)	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
League Position (Away)	0.106***	0.037***	0.032***	0.042***	0.065***	0.085***	0.106***	0.141***
	(0.001)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Total Goals Scored (Home)	-0.001***	-0.001	-0.001	-0.001	0.001*	0.001	-0.000	-0.001*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Total Goal Difference (Home)	0.017***	0.007***	0.010***	0.011***	0.011***	0.009***	0.012***	0.013***
	(0.000)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-2.107***	-0.455**	-0.881***	-1.514***	-1.541***	-2.131***	-2.347***	-2.605***
	(0.028)	(0.204)	(0.153)	(0.119)	(0.086)	(0.068)	(0.069)	(0.060)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626
R-squared	0.145	0.047	0.045	0.069	0.105	0.140	0.163	0.155
Number of team1id	4,937	70	104	188	325	624	777	1,810
Adjusted R-squared	0.134	0.0332	0.0335	0.0574	0.0946	0.131	0.152	0.140

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

On-pitch performance gives a somewhat different view of fan-owned clubs (Table 3.6-3.11.). Overall, having a fan-owned club seems to add 4 goals per season to the club's performance, when taken across all steps, although this is not significant. What is, significant, is that in Step 1, it can essentially cause a club a large deficit (with a –0.715 coefficient). On balance, this negative effect reduces drastically across the other steps but is not significant, suggesting broadly that having a fan-owned club is not going to drastically increase on-pitch performance in terms of home goals alone. The main predictor, of Home Goals, is the Elo rating which is incredibly powerful. For the effect on away goals across all steps there is a potential reduction in away goals with this being the case in Steps 2,3, 5 & 6. What confirms all this though, is the section on Goal Difference (this is goal difference in the match itself, so if the home club wins 4-1, the goal difference is 3), Which starts to firm-up the theory that fan-owned clubs can peak at certain points. Clubs at Step 7 or 8 and through Step 4 perform well when compared to non-fan owned clubs, after this point, they encounter a much higher and less purely regional club. At Step 1 a similar effect occurs, where it appears the clubs simply cannot compete where the league can be quite imbalanced, if a club with a substantially smaller budget is fan-owned in that league, compared with most clubs being professional and clubs that are not fully so, or have less resources, struggling, we would expect them to struggle.

Table 3.9. Outcome Home Win with Fan Owned Clubs plus controls

VARIABLES	(1) All Steps Outcome Home Win	(2) Step 1 Outcome Home Win	(3) Step 2 Outcome Home Win	(4) Step 3 Outcome Home Win	(5) Step 4 Outcome Home Win	(6) Step 5 Outcome Home Win	(7) Step 6 Outcome Home Win	(8) Step 7 Outcome Home Win
Fan Owned Match	0.035**	-0.116	0.027	0.053	-0.109**	0.020	0.041	0.054
	(0.016)	(0.078)	(0.057)	(0.043)	(0.049)	(0.044)	(0.119)	(0.062)
Elopredict	0.526***	0.305***	0.469***	0.474***	0.460***	0.530***	0.526***	0.519***
	(0.008)	(0.099)	(0.065)	(0.048)	(0.030)	(0.022)	(0.019)	(0.017)
League Position (Home)	-0.006***	-0.000	0.004**	0.001	-0.001	-0.000	-0.004***	-0.002***
	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
League Position (Away)	0.017***	0.009***	0.007***	0.009***	0.012***	0.015***	0.017***	0.022***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Goal Scored per game (Home)	0.008***	-0.008	0.005	0.020	0.018**	-0.006	-0.004	-0.006*
	(0.002)	(0.025)	(0.018)	(0.013)	(0.009)	(0.006)	(0.005)	(0.003)
Goal Diff per game (Home)	0.037***	0.047**	0.065***	0.034***	0.043***	0.058***	0.042***	0.042***
	(0.001)	(0.021)	(0.014)	(0.011)	(0.007)	(0.004)	(0.003)	(0.002)
Constant	0.069***	0.200***	0.082	0.029	0.034	0.015	0.030*	0.020
	(0.007)	(0.072)	(0.052)	(0.038)	(0.026)	(0.018)	(0.017)	(0.013)
Observations	398,880	6,001	9,747	16,895	29,032	58,130	61,164	101,387
R-squared	0.100	0.031	0.034	0.041	0.070	0.094	0.111	0.101
Number of team1id	4,923	70	104	188	325	620	777	1,808
Adjusted R-squared	0.0888	0.0171	0.0217	0.0295	0.0592	0.0837	0.0991	0.0844

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 3.10. Outcome Draw with Fan Owned Clubs plus controls

VARIABLES	(1) All Steps Outcome Draw	(2) Step 1 Outcome Draw	(3) Step 2 Outcome Draw	(4) Step 3 Outcome Draw	(5) Step 4 Outcome Draw	(6) Step 5 Outcome Draw	(7) Step 6 Outcome Draw	(8) Step 7 Outcome Draw
Fan Owned Match	-0.021	0.020	-0.038	-0.011	0.038	-0.002	-0.008	-0.074
	(0.013)	(0.069)	(0.050)	(0.037)	(0.041)	(0.036)	(0.095)	(0.050)
Elopredict	-0.026***	0.056	-0.093	-0.072*	-0.062**	-0.027	-0.058***	-0.009
	(0.007)	(0.090)	(0.058)	(0.042)	(0.026)	(0.018)	(0.015)	(0.013)
League Position (Home)	0.000	0.000	-0.000	-0.000	-0.000	-0.001**	-0.001	-0.001*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
League Position (Away)	-0.001***	-0.002**	-0.000	-0.001**	-0.001***	-0.001**	-0.001***	-0.001***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Total Goals Scored (Home)	0.000***	-0.000	0.000	-0.000	-0.000*	0.000	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Goal Difference (Home)	-0.000*	0.000	-0.000	0.001*	0.000	-0.000*	0.000	-0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.199***	0.269***	0.286***	0.294***	0.277***	0.213***	0.233***	0.195***
	(0.004)	(0.054)	(0.037)	(0.027)	(0.017)	(0.012)	(0.011)	(0.009)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626
R-squared	0.001	0.003	0.003	0.002	0.002	0.001	0.001	0.001
Number of team1id	4,937	70	104	188	325	624	777	1,810
Adjusted R-squared	-0.0115	-0.0113	-0.00875	-0.0100	-0.00989	-0.0100	-0.0115	-0.0166

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 3.11. Outcome Away Win with Fan Owned Clubs plus controls

VARIABLES	(1) All Steps Outcome Away Win	(2) Step 1 Outcome Away Win	(3) Step 2 Outcome Away Win	(4) Step 3 Outcome Away Win	(5) Step 4 Outcome Away Win	(6) Step 5 Outcome Away Win	(7) Step 6 Outcome Away Win	(8) Step 7 Outcome Away Win
Fan Owned Match	-0.009	0.116	0.023	-0.043	0.072	0.002	-0.050	0.050
	(0.015)	(0.072)	(0.053)	(0.041)	(0.047)	(0.043)	(0.115)	(0.061)
Elopredict	-0.496***	-0.310***	-0.342***	-0.403***	-0.391***	-0.521***	-0.480***	-0.531***
	(0.008)	(0.094)	(0.062)	(0.046)	(0.029)	(0.022)	(0.019)	(0.016)
League Position (Home)	0.008***	0.001	0.001	0.001	0.004***	0.006***	0.007***	0.007***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
League Position (Away)	-0.015***	-0.006***	-0.006***	-0.007***	-0.011***	-0.013***	-0.015***	-0.020***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Total Goals Scored (Home)	0.000**	0.001**	-0.000	0.000	0.000	-0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Goal Difference (Home)	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.688***	0.498***	0.548***	0.635***	0.635***	0.736***	0.717***	0.752***
	(0.005)	(0.056)	(0.040)	(0.029)	(0.020)	(0.014)	(0.013)	(0.011)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626
R-squared	0.091	0.026	0.026	0.038	0.060	0.084	0.099	0.094
Number of team1id	4,937	70	104	188	325	624	777	1,810
Adjusted R-squared	0.0797	0.0123	0.0139	0.0265	0.0495	0.0744	0.0880	0.0783

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 3.9., Outcome Home Win, suggests that the idea that fan-owned clubs can have some success at the lower levels is borne out (although the evidence is not strong), at steps 5-7 a club could see between a 2-5% extra chance of a home win from being a fan-owned club, this is then repeated at Step 2 and 3, this should be treated with a bit of caution though along with the previous review of the effect on home goals. The effects on an away win, show similar results, with Step 1 & 4 again being the step where a fan-own club is more likely to struggle with an away win being between 7% (Step 4) and 11% (Step 1) more likely to occur.

Of the various independent variables Elo rating is still a strong predictor of match outcomes as are away goals and goal difference. These independent variables have more consistent predictive strength or are more closely correlated to determining attendance or match outcomes than some of the other variables we include as controls.

3.5 Conclusion

Our results find that there are some benefits at the grassroots level to a football club being community owned or 'fan-owned'. There appear to be some improvements to attendance but also on-pitch performance. What we don't know is enough about other unknown factors that could be driving attendance at the lowest levels or on pitch performances, although outcome uncertainty and expectation of a home win appear strong drivers still. What we can tell though is that a fan-owned club appears to perform better in terms of home wins, to the degree of between 2-5% depending on whether the club is in either Steps 2-3 or Steps 5-7. Outside of those Steps, there doesn't seem to be a benefit to home wins. A club with a 5% home win advantage would expect to win an extra home game per season in a 38-game season (with 19 home games). In terms of home goals scored, though the advantages are only evident at Steps 3 and 7 where there is a 3 (Step 3) - 30% (Step7) increase in goals for fan owned clubs but this is not statistically significant.

In addition, clubs playing at Steps 2, 3 & 5, should expect to gain between a 10-30% increase in home attendance if they are fan-owned. Attendances for fan owned clubs in the top Step, the National League though are at an almost 50% disadvantage, which may also help to explain the on-pitch performance differences (if we accept that revenue difference over time would affect performances).

These results indicate that there may be a benefit to fan ownership that is worth encouraging and certainly that is worth greater exploration. Future research should consider examining a number of specific leagues that in a given season have sufficient enough clubs within them. In the last few years there has been policy interest from the UK government and opposition parties in the subject of football ownership, as evidence by the Fan-Led Review that both the current and previous government have taken interest in, in terms of developing legislation and potentially bringing in greater regulation over club ownership.[45] Our findings suggest that fan-ownership models may have some benefits that are additional to whether the model itself is a more nebulous, moral type for clubs to aim for, which we are not examining. Compared to other clubs in the non-league structure though, from an economic and performance point of view, there also may be a limited financial benefit to increasing attendances at the lowest levels in conjunction with an on-pitch opportunity to gain advantage compared to other clubs in non-league football, at least at the lower and mid-range Steps.

[45] https://www.gov.uk/government/publications/fan-led-review-of-football-governance-securing-the-games-future/fan-led-review-of-football-governance-securing-the-games-future Accessed 2/9/2024

4.1. Overall Conclusion

The aim of this thesis has been to use data from fans attending football matches to test whether different policy decisions made either by governments and football regulatory bodies or agencies and by football clubs have affected outcomes either on or off the pitch.

The first Chapter, on the spread of Covid-19 and fans attending football matches, demonstrates the need for future governments to consider behaviours at large scale events as potential super-spreaders, even where the event takes place largely outside.

In this first Chapter, we find that fans attending matches appear to have increased the spread of Covid-19 in February and March of 2020 and that this led to an increase in deaths, excess deaths and Covid-19 cases. We have contributed to the literature on pandemics and sports attendance at mass outdoor events. This is one of the first papers to show linkages between outdoor events and airborne viruses, as fans still come into contact with each other in indoor settings (travelling to games, meeting before and after and at half-time). We acknowledge there are limits to this data and that whilst we expect the most likely causation of the increase in cases, deaths and excess deaths is either fans travelling to and from matches or congregating before during and after matches and we do not know the exact cause within this sub-group, our results indicate it is match attendance related.

The second Chapter, tests to see whether 3G pitches at the grassroots level have an impact on attendances and match outcomes. It shows that the effects of 3G pitches are minimal except in some cases, mainly in terms of additional goals scored over time at the very lowest levels, where quality is reduced. We did initially seem to find some strong effects on attendance and home performance with the first set of Football Foundation data from the 2022 season but once we expanded this to include any club that had had a 3G pitch between 2011-2023 and across all Steps, these attendance effects in particular were largely removed. Overall, in Chapter Two, we find that the effect of having a 3G pitches is minimal in terms of either increasing attendances, or on-pitch performance. There does however seem to be a positive effect on attendance at Step 7 and 8 but this should be treated with some caution, due to gaps in the data recording and nature of that level of participation. Further research is needed into what determines how random or not it is whether a club has a 3G pitch or not and whether it is down to financial resource or that clubs that are high performing are more likely to have better internal management and this is why they succeed in getting additional funding. There is interest from policy makers and sports funding bodies in this subject and that whilst there is acknowledgement of the environmental impact of installing a pitch, there is also the health impact of postponing matches and access to sporting facilities (Sport England, 2024).[46] This makes examining the value of this type of pitch to football clubs an important subject to study further, in the ways we have demonstrated, as even small benefits to lower level clubs will be of interest. They are expensive to install though and although there may be benefits from lack of match postponement or increased revenue, we do not include this data so cannot examine that effect and thus justify the expense based on our data.

The third Chapter, on fan-ownership of football clubs also uses attendances to see if fan owned clubs gain any benefit financially and whether they receive any on-field advantage. We find that in contrast to the effect of having a 3G pitch, a non-league club that is owned by the fans has some clearer benefits in terms of increased number of home wins firstly at Steps 5-7 and then between Steps 2-3. There also is an attendance advantage for fan-owned clubs to the level of 10-30% but only at Steps 2,3

[46] https://www.theguardian.com/sport/2023/oct/11/sport-england-tells-sports-fight-climate-crisis-or-youll-get-no-funding (accessed 14/9/2024) Chair of Sport England, Chris Boardman, acknowledges the effect of 3G pitches on the environment but contrasts with a third of community pitches are already unplayable for two months of the year due to flooding https://www.sportengland.org/news-and-inspiration/major-investment-help-sports-battle-climate-change (accessed 14/9/2024)

& 5. We find however, that fan-owned clubs compared to others in the Step, do not have a goal difference advantage to any consistency. Both the second and third Chapter contribute to literature on outcome uncertainty and attendance demand in football, showing that there are other factors in particular the ownership of clubs, that can impact on what determines fan attendance and club on-pitch performance. Further research is needed into the determining factors for why a club becomes fan owned, such as how random they are and how many fan owned clubs start with a resource advantage, when compared to other clubs in their leagues, either because of them having a previously rich football history or that they retain professional level resources such as stadia and staff before fans take over.

Overall, we have demonstrated that a number of football related policy decisions can affect either public health outcomes or alternatively affect attendance at matches and affect performance either to a minor or in some cases potentially valuable extent.

Whilst decisions made in a pandemic situation can clearly be life or death, the other level of decisions we have studied, at the football club and league structure level can affect club performance either financially, on the pitch or both. Regulatory issues relating to ownership of clubs and type of facilities they can use are of current interest to stakeholders such as fans and clubs but also important to policy makers.

References

AHAMMER, A., HALLA, M. & LACKNER, M. 2020. Mass gatherings contributed to early COVID-19 spread: Evidence from US sports. Working paper.

BAI, Y., YAO, L., WEI, T., TIAN, F., JIN, D.-Y., CHEN, L. & WANG, M. 2020. Presumed asymptomatic carrier transmission of COVID-19. *Jama,* 323, 1406-1407.

BARNETT, V. & HILDITCH, S. 1993. The Effect of an Artificial Pitch Surface on Home Team Performance in Football (Soccer). *Journal of the Royal Statistical Society. Series A (Statistics in Society),* 156, 39-50.

BAUERS, S. B., LAMMERT, J., FAIX, A. & HOVEMANN, G. 2020. Club members in German professional football and their attitude towards the '50+1 Rule' – A stakeholder-oriented analysis. *Soccer & Society,* 21, 274-288.

BECKER, G. S. 2011. CEP Discussion Paper No 1079 September 2011 Fear and the Response to Terrorism: An Economic Analysis Gary S. Becker and Yona Rubinstein.

BURAIMO, B. & SIMMONS, R. 2015. Uncertainty of Outcome or Star Quality? Television Audience Demand for English Premier League Football. *International Journal of the Economics of Business,* 22, 449-469.

BURAIMO, B., TENA, J. D. & DE LA PIEDRA, J. D. 2018. Attendance demand in a developing football market: the case of the Peruvian first division. *European Sport Management Quarterly,* 18, 671-686.

BURILLO, P., GALLARDO, L., FELIPE, J. L. & GALLARDO, A. M. 2014. Artificial turf surfaces: Perception of safety, sporting feature, satisfaction and preference of football users. *European Journal of Sport Science,* 14, S437-S447.

BUZZACCHI, L., SZYMANSKI, S. & VALLETTI, T. M. 2003. Equality of Opportunity and Equality of Outcome: Open Leagues, Closed Leagues and Competitive Balance *#We thank the Editor and an anonymous referee for helpful comments. *Journal of Industry, Competition and Trade,* 3, 167-186.

CALLOWAY, S. P., HARDIN, D. M., CRAWFORD, M. D., HARDIN, J. M., LEMAK, L. J., GIZA, E., FORSYTHE, B., LU, Y., PATEL, B. H. & OSBAHR, D. C. 2019. Injury surveillance in major league soccer: a 4-year comparison of injury on natural grass versus artificial turf field. *The American journal of sports medicine,* 47, 2279-2286.

CARDAZZI, A., HUMPHREYS, B. R., RUSESKI, J. E., SOEBBING, B. & WATANABE, N. 2020. Professional Sporting Events Increase Seasonal Influenza Mortality in US Cities. *Available at SSRN 3628649*.

CHABROS, M. A., D; JONES, C; OLCZAK, M 2019. The Determinants of Grassroots English Football

Attendance, Working Paper. University of Aston.

CHENG, H., HU, Y. & REINHARD, M. 2014. Environmental and health impacts of artificial turf: a review. *Environmental science & technology,* 48, 2114-2129.

COATES, D. & HUMPHREYS, B. R. 2010. Week to week attendance and competitive balance in the National Football League. *International Journal of Sport Finance,* 5, 239.

COATES, D. & HUMPHREYS, B. R. 2012. Game Attendance and Outcome Uncertainty in the National Hockey League. *Journal of Sports Economics,* 13, 364-377.

COUSINS, B. E. W., MORRIS, J. G., SUNDERLAND, C., BENNETT, A. M., SHAHTAHMASSEBI, G. & COOPER, S. B. 2022. Synthetic playing surfaces increase the incidence of match injuries in an elite Rugby Union team. *Journal of Science and Medicine in Sport,* 25, 134-138.

COX, A. 2012. Live Broadcasting, Gate Revenue, and Football Club Performance: Some Evidence. *International Journal of the Economics of Business,* 19, 75-98.

DOBSON, S. M. & GODDARD, J. A. 1996. The Demand for Football in the Regions of England and Wales. *Regional Studies,* 30, 443-453.

EKSTRAND, J., TIMPKA, T. & HÄGGLUND, M. 2006. Risk of injury in elite football played on artificial turf versus natural grass: a prospective two-cohort study. *British journal of sports medicine,* 40, 975-980.

FISCHER, K. 2021. Thinning out Spectators: Did Football Matches Contribute to the Second COVID-19 Wave in Germany? *Available at SSRN 3793379*.

FLEMING, P. 2011. Artificial turf systems for sport surfaces: current knowledge and research needs. *Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology,* 225, 43-63.

FORREST, D., BEAUMONT, J., GODDARD, J. & SIMMONS, R. 2005a. Home advantage and the debate about competitive balance in professional sports leagues. *Journal of Sports Sciences,* 23, 439-445.

FORREST, D. & SIMMONS, R. 2002a. Outcome uncertainty and attendance demand in sport: the case of English soccer. *Journal of the Royal Statistical Society: Series D (The Statistician),* 51, 229-241.

FORREST, D. & SIMMONS, R. 2002b. Outcome Uncertainty and Attendance Demand in Sport: The Case of English Soccer. *Journal of the Royal Statistical Society. Series D (The Statistician),* 51, 229-241.

FORREST, D. & SIMMONS, R. 2006. New issues in attendance demand: The case of the English football league. *Journal of Sports Economics,* 7, 247-266.

FORREST, D., SIMMONS, R. & BURAIMO, B. 2005b. Outcome uncertainty and the couch potato audience. *Scottish Journal of Political Economy,* 52, 641-661.

GARCÍA, J. & RODRÍGUEZ, P. 2002. The determinants of football match attendance revisited: Empirical evidence from the Spanish football league. *Journal of Sports Economics,* 3, 18-38.

GITTER, S. R. 2017. The H1N1 Virus and Mexican Baseball Attendance. *Athens Journal of Sports,* 4.

GOULD, H. P., LOSTETTER, S. J., SAMUELSON, E. R. & GUYTON, G. P. 2023. Lower Extremity Injury Rates on Artificial Turf Versus Natural Grass Playing Surfaces: A Systematic Review. *The American Journal of Sports Medicine,* 51, 1615-1621.

GRANERO-GIL, P., BASTIDA-CASTILLO, A., ROJAS-VALVERDE, D., GÓMEZ-CARMONA, C. D., DE LA CRUZ SÁNCHEZ, E. & PINO-ORTEGA, J. 2020. Influence of Contextual Variables in the Changes of Direction and Centripetal Force Generated during an Elite-Level Soccer Team Season. *International Journal of Environmental Research and Public Health,* 17, 967.

HAMNER, L. 2020. High SARS-CoV-2 attack rate following exposure at a choir practice—Skagit County, Washington, March 2020. *MMWR. Morbidity and mortality weekly report,* 69.

HART, R. A., HUTTON, J. & SHAROT, T. 1975. A Statistical Analysis of Association Football Attendances. *Journal of the Royal Statistical Society: Series C (Applied Statistics),* 24, 17-27.

HOGAN, V., MASSEY, P. & MASSEY, S. 2017. Analysing match attendance in the European Rugby Cup: Does uncertainty of outcome matter in a multinational tournament? *European Sport Management Quarterly,* 17, 312-330.

HUMPHREYS, B. R. & ZHOU, L. 2015. The Louis–Schmelling Paradox and the League Standing Effect Reconsidered. *Journal of Sports Economics,* 16, 835-852.

HVATTUM, L. M. & ARNTZEN, H. 2010. Using ELO ratings for match result prediction in association football. *International Journal of Forecasting,* 26, 460-470.

KENNEDY, P. & KENNEDY, D. 2012. Football supporters and the commercialisation of football: comparative responses across Europe. *Soccer & Society,* 13, 327-340.

KUO, H.-I., CHANG, C.-L., HUANG, B.-W., CHEN, C.-C. & MCALEER, M. 2009. Estimating the Impact of Avian Flu on International Tourism Demand Using Panel Data. *Tourism Economics,* 15, 501-511.

KUO, H.-I., CHEN, C.-C., TSENG, W.-C., JU, L.-F. & HUANG, B.-W. 2008. Assessing impacts of SARS and Avian Flu on international tourism demand to Asia. *Tourism Management,* 29, 917-928.

LARSSON, A., RANUDD, E., RONCHI, E., HUNT, A. & GWYNNE, S. 2021. The impact of crowd composition on egress performance. *Fire Safety Journal,* 120, 103040.

LAUER, S. A., GRANTZ, K. H., BI, Q., JONES, F. K., ZHENG, Q., MEREDITH, H. R., AZMAN, A. S., REICH, N. G. & LESSLER, J. 2020. The incubation period of coronavirus disease 2019 (COVID-19) from publicly reported confirmed cases: estimation and application. *Annals of internal medicine,* 172, 577-582.

LEAN, H. H. & SMYTH, R. 2009. Asian financial crisis, avian flu and terrorist threats: are shocks to Malaysian tourist arrivals permanent or transitory? *Asia Pacific Journal of Tourism Research,* 14, 301-321.

MAO, C.-K., DING, C. G. & LEE, H.-Y. 2010. Post-SARS tourist arrival recovery patterns: An analysis based on a catastrophe theory. *Tourism Management,* 31, 855-861.

MARTINS, A. M. & CRÓ, S. 2018. The Demand for Football in Portugal:New Insights on Outcome Uncertainty. *Journal of Sports Economics,* 19, 473-497.

MAY, A. & PARNELL, D. 2017. The community impact of football pitches: a case study of Maidstone United FC. *Sport in Society,* 20, 244-257.

NEALE, W. C. 1964. The peculiar economics of professional sports. *The quarterly journal of economics,* 78, 1-14.

NIELSEN, C. G., STORM, R. K. & JAKOBSEN, T. G. 2019. The impact of English Premier League broadcasts on Danish spectator demand: a small league perspective. *Journal of Business Economics,* 89, 633-653.

NOLL, R. G. 2002. The Economics of Promotion and Relegation in Sports Leagues:The Case of English Football. *Journal of Sports Economics,* 3, 169-203.

OWEN, P. D. & WEATHERSTON, C. R. 2004. Uncertainty of outcome and super 12 rugby union attendance: Application of a general-to-specific modeling strategy. *Journal of Sports Economics,* 5, 347-370.
OZAYDIN, S. & DONDURAN, M. 2019. An Empirical Study of Revenue Generation and Competitive Balance Relationship in European Football. *Eurasian Journal of Business and Economics,* 12, 17-44.
PATON, D. & COOKE, A. 2005. Attendance at county cricket: An economic analysis. *Journal of Sports Economics,* 6, 24-45.
PAWLOWSKI, T. & ANDERS, C. 2012. Stadium attendance in German professional football – the (un)importance of uncertainty of outcome reconsidered. *Applied Economics Letters,* 19, 1553-1556.
PEEL, D. & THOMAS, D. 1996. Attendance demand: An investigation of repeat fixtures. *Applied Economics Letters,* 3, 391-394.
PEETERS, T. & VAN OURS, J. C. 2021. Seasonal Home Advantage in English Professional Football; 1974–2018. *De Economist,* 169, 107-126.
POLLARD, R. 1986. Home advantage in soccer: A retrospective analysis. *Journal of Sports Sciences,* 4, 237-248.
POTTHAST, W., VERHELST, R., HUGHES, M., STONE, K. & DE CLERCQ, D. 2010. Football-specific evaluation of player–surface interaction on different football turf systems. *Sports Technology,* 3, 5-12.
PRONK, M. E. J., WOUTERSEN, M. & HERREMANS, J. M. M. 2020. Synthetic turf pitches with rubber granulate infill: are there health risks for people playing sports on such pitches? *Journal of Exposure Science & Environmental Epidemiology,* 30, 567-584.
RASSY, D. & SMITH, R. D. 2013. The economic impact of H1N1 on Mexico's tourist and pork sectors. *Health economics,* 22, 824-834.
READE, J. J. 2021. Football attendance over the centuries. *A Modern Guide to Sports Economics*, 21-43.
READE, J. J., SCHREYER, D. & SINGLETON, C. 2020. Stadium attendance demand during the COVID-19 crisis: Early empirical evidence from Belarus. *Applied Economics Letters*, 1-6.
READE, J. J., SCHREYER, D. & SINGLETON, C. 2022. Eliminating supportive crowds reduces referee bias. *Economic Inquiry,* 60, 1416-1436.
READE, J. J. & SINGLETON, C. 2020. Demand for Public Events in the COVID-19 Pandemic: A Case Study of European Football. Henley Business School, Reading University.
REILLY, B. 2015. The demand for league of Ireland football. *The Economic and Social Review,* 46, 485–509-485–509.
ROHDE, M. & BREUER, C. 2018. Competing by investments or efficiency? Exploring financial and sporting efficiency of club ownership structures in European football. *Sport Management Review,* 21, 563-581.
SASSANO, M., MCKEE, M., RICCIARDI, W. & BOCCIA, S. 2020. Transmission of SARS-CoV-2 and other infections at large sports gatherings: a surprising gap in our knowledge. *Frontiers in medicine,* 7, 277.
SCELLES, N., DURAND, C., BONNAL, L., GOYEAU, D. & ANDREFF, W. 2013. Competitive balance versus competitive intensity before a match: is one of these two

concepts more relevant in explaining attendance? The case of the French football Ligue 1 over the period 2008–2011. *Applied Economics,* 45, 4184-4192.
SCHLESINGER, T. & NAGEL, S. 2013. Who will volunteer? Analysing individual and structural factors of volunteering in Swiss sports clubs. *European Journal of Sport Science,* 13, 707-715.
SEMMELROTH, D., FRICK, B., SIMMONS, R. & SUNG, H. 2022. Where to go next? Examining the effect of franchise expansion and location on game-level attendance in Major League Soccer. *Journal of Sports Economics,* 23, 524-547.
SERRANO, R., GARCÍA-BERNAL, J., FERNÁNDEZ-OLMOS, M. & ESPITIA-ESCUER, M. A. 2015. Expected quality in European football attendance: market value and uncertainty reconsidered. *Applied Economics Letters,* 22, 1051-1054.
SIMMONS, R. 1996. The demand for English league football: a club-level analysis. *Applied Economics,* 28, 139-155.
SLOANE, P. J. 1971. SCOTTISH JOURNAL OF POLITICAL ECONOMY:THE ECONOMICS OF PROFESSIONAL FOOTBALL: THE FOOTBALL CLUB AS A UTILITY MAXIMISER*. *Scottish Journal of Political Economy,* 18, 121-146.
SOEBBING, B. P. 2008. Competitive balance and attendance in Major League Baseball: An empirical test of the uncertainty of outcome hypothesis. *International Journal of Sport Finance,* 3, 119.
SPORT ENGLAND. 2023. *Active Places, Active Power - archive, open data* [Online]. Available: https://www.activeplacespower.com/opendata [Accessed 03/10/2023].
SPORT ENGLAND. 2024. *Major investment to help sports battle climate change* [Online]. Sport England,. Available: https://www.sportengland.org/news-and-inspiration/major-investment-help-sports-battle-climate-change [Accessed 16/9/2024].
STOECKER, C., SANDERS, N. J. & BARRECA, A. 2016. Success Is something to sneeze at: Influenza mortality in cities that participate in the Super Bowl. *American Journal of Health Economics,* 2, 125-143.
SZYMANSKI, S. 2001. Income inequality, competitive balance and the attractiveness of team sports: Some evidence and a natural experiment from English soccer. *The Economic Journal,* 111, F69-F84.
SZYMANSKI, S. & SMITH, R. 1997. The English Football Industry: profit, performance and industrial structure. *International Review of Applied Economics,* 11, 135-153.
SZYMANSKI, S., SZYMANSKI, S. & VALLETTI, T. M. 2010. Promotion and relegation in sporting contests. *The comparative economics of sport*, 198-228.
THE FOOTBALL SUPPPORTERS ASSOCIATION. 2021. *The Football Suppporters Association* [Online]. Available: https://thefsa.org.uk/about/ [Accessed 16/09/21].
THIEL, A. & MAYER, J. 2009. Characteristics of Voluntary Sports Clubs Management: a Sociological Perspective. *European Sport Management Quarterly,* 9, 81-98.
TORCHIA, D. 2016. An alternative football club in a liquid modernity: FC United of Manchester. *Culture and organization,* 22, 203-220.
TWOMEY, D. M., PETRASS, L. A., FLEMING, P. & LENEHAN, K. 2019. Abrasion injuries on artificial turf: A systematic review. *Journal of Science and Medicine in Sport,* 22, 550-556.

UHRICH, S. 2021. Antecedents and consequences of perceived fan participation in the decision making of professional European football clubs. *European Sport Management Quarterly,* 21, 504-523.

ULAS, E. 2021. Examination of National Basketball Association (NBA) team values based on dynamic linear mixed models. *PLoS one,* 16, e0253179.

VAN OURS, J. C. 2019. A Note on Artificial Pitches and Home Advantage in Dutch Professional Football. *De Economist,* 167, 89-103.

VROOMAN, J. 2000. The Economics of American Sports Leagues. *Scottish Journal of Political Economy,* 47, 364-398.

VROOMAN, J. 2011. The economic structure of the NFL. *The economics of the National Football League: The state of the art.* Springer.

WALLRAFEN, T., PAWLOWSKI, T. & DEUTSCHER, C. 2019. Substitution in Sports: The Case of Lower Division Football Attendance. *Journal of Sports Economics,* 20, 319-343.

WANG, C. C., PRATHER, K. A., SZNITMAN, J., JIMENEZ, J. L., LAKDAWALA, S. S., TUFEKCI, Z. & MARR, L. C. 2021. Airborne transmission of respiratory viruses. *Science,* 373, eabd9149.

WARD, S. & HINES, A. 2017. The demise of the members' association ownership model in German professional football. *Managing Sport and Leisure,* 22, 358-373.

WARD, S., SCANLON, T. J. & HINES, T. 2013. Mutuality Ownership Form and Professional Sports:Football. *Nonprofit and Voluntary Sector Quarterly,* 42, 763-780.

WARREN, C. R. & MCFADYEN, M. 2010. Does community ownership affect public attitudes to wind energy? A case study from south-west Scotland. *Land Use Policy,* 27, 204-213.

WATKINS, L. & COX, L. 2020. The limits of loyalty to professional football teams and the attraction of non-league football: A case study of Worcester City FC. *Soccer & Society*, 1-16.

WILLIAMS, J. & CAULFIELD, P. 2020. 'Why do I want to go and watch that?' English non-league football fans in the Premier League era. *Sport in Society,* 23, 901-919.

WILSON, P. & SIM, B. 1995. The demand for semi-pro league football in Malaysia 1989–91: A panel data approach. *Applied Economics,* 27, 131-138.

WILSON, R. & PLUMLEY, D. 2017. Different shaped ball, same financial problems? A holistic performance assessment of English Rugby Union (2006-2015). *Sport, Business and Management: An International Journal,* 7, 141-156.

XIAO, M., LEMOS, J. L., HWANG, C. E., SHERMAN, S. L., SAFRAN, M. R. & ABRAMS, G. D. 2022. Increased Risk of ACL Injury for Female but Not Male Soccer Players on Artificial Turf Versus Natural Grass: A Systematic Review and Meta-Analysis. *Orthopaedic Journal of Sports Medicine,* 10, 23259671221114353.

Appendix 1. Additional Tables from Chapter 2

Additional Tables are listed below for completeness but were removed from the main paper as they don't really tell us much more than the 'outcome home win' does for each type of regression.

Table 2.14. Outcome draw (original Football Foundation), with controls and fixed effects.

VARIABLES	(1) All Steps Outcome Draw	(2) Step 1 Outcome Draw	(3) Step 2 Outcome Draw	(4) Step 3 Outcome Draw	(5) Step 4 Outcome Draw	(6) Step 5 Outcome Draw	(7) Step 6 Outcome Draw	(8) Step 7 Outcome Draw	(9) Step 8 Outcome Draw	(10) Step 9 Outcome Draw
FF 3G Pitch for Match	-0.002	0.120*	0.073***	-0.019	0.004	-0.039**	-0.000	-0.035	-0.079**	0.033
	(0.006)	(0.068)	(0.024)	(0.018)	(0.016)	(0.015)	(0.017)	(0.024)	(0.032)	(0.365)
Elopredict	-0.026***	0.054	-0.100*	-0.071*	-0.063**	-0.027	-0.058***	-0.010	-0.034**	-0.011
	(0.007)	(0.090)	(0.058)	(0.042)	(0.026)	(0.018)	(0.015)	(0.013)	(0.017)	(0.044)
League Position (Home)	0.000	0.000	-0.000	-0.000	-0.000	-0.001**	-0.001	-0.001*	-0.001**	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
League Position (Away)	-0.001***	-0.002**	-0.000	-0.001**	-0.001***	-0.001**	-0.001***	-0.001***	-0.001***	-0.001*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Total Goals Scored (Home)	0.000***	-0.000	0.000	-0.000	-0.000*	0.000	-0.000	0.000***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Goal Difference (Home)	-0.000*	0.000	-0.000	0.001*	0.000	-0.000*	0.000	-0.000	-0.000***	0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.199***	0.263***	0.284***	0.296***	0.278***	0.215***	0.233***	0.196***	0.203***	0.112***
	(0.004)	(0.053)	(0.037)	(0.027)	(0.017)	(0.012)	(0.011)	(0.009)	(0.011)	(0.033)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626	93,782	17,311
R-squared	0.001	0.004	0.004	0.002	0.002	0.001	0.001	0.001	0.002	0.004
Number of team1id	4,937	70	104	188	325	624	777	1,810	2,788	821
Adjusted R-squared	-0.0115	-0.0108	-0.00783	-0.00999	-0.00992	-0.00993	-0.0115	-0.0166	-0.0287	-0.0472

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and weekday

Table 2.15. Outcome away win (original Football Foundation), with controls and fixed effects.

VARIABLES	(1) All Steps Away Win	(2) Step 1 Away Win	(3) Step 2 Away Win	(4) Step 3 Away Win	(5) Step 4 Away Win	(6) Step 5 Away Win	(7) Step 6 Away Win	(8) Step 7 Away Win	(9) Step 8 Away Win	(10) Step 9 Away Win
FF 3G Pitch for Match	-0.026***	-0.132*	-0.010	-0.022	-0.078***	-0.013	-0.016	-0.098***	-0.125***	0.226
	(0.007)	(0.071)	(0.025)	(0.020)	(0.018)	(0.018)	(0.020)	(0.029)	(0.038)	(0.444)
Elopredict	-0.496***	-0.309***	-0.339***	-0.402***	-0.389***	-0.521***	-0.481***	-0.532***	-0.544***	-0.478***
	(0.008)	(0.094)	(0.061)	(0.046)	(0.029)	(0.022)	(0.019)	(0.016)	(0.020)	(0.054)
League Position (Home)	0.008***	0.001	0.001	0.001	0.004***	0.006***	0.007***	0.007***	0.007***	0.006***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)
League Position (Away)	-0.015***	-0.006***	-0.006***	-0.007***	-0.011***	-0.013***	-0.015***	-0.020***	-0.023***	-0.026***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Total Goals Scored (Home)	0.000**	0.001**	-0.000	0.000	0.000	-0.000**	0.000	0.000	-0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Goal Difference (Home)	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.001***	-0.002***	-0.002***	-0.001***	-0.001***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.689***	0.521***	0.549***	0.634***	0.643***	0.737***	0.718***	0.754***	0.777***	0.830***
	(0.005)	(0.056)	(0.040)	(0.029)	(0.020)	(0.014)	(0.013)	(0.011)	(0.013)	(0.040)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626	93,782	17,311
R-squared	0.091	0.026	0.026	0.038	0.061	0.084	0.099	0.094	0.085	0.075
Number of team1id	4,937	70	104	188	325	624	777	1,810	2,788	821
Adjusted R-squared	0.0797	0.0124	0.0139	0.0265	0.0500	0.0744	0.0880	0.0784	0.0565	0.0280

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and weekday

Table 2.21. Outcome Draw (Clubs with any kind of 3G pitch – for use in competitive matches or for training purposes only)

VARIABLES	(1) All Steps Outcome Draw	(2) Step 1 Outcome Draw	(3) Step 2 Outcome Draw	(4) Step 3 Outcome Draw	(5) Step 4 Outcome Draw	(6) Step 5 Outcome Draw	(7) Step 6 Outcome Draw	(8) Step 7 Outcome Draw	(9) Step 8 Outcome Draw	(10) Step 9 Outcome Draw
3G Training and match use	-0.005	-0.047	0.047**	-0.021	-0.013	0.005	-0.009	-0.008	-0.013	-0.019
	(0.006)	(0.040)	(0.021)	(0.016)	(0.013)	(0.012)	(0.015)	(0.018)	(0.028)	(0.050)
Elopredict	-0.026***	0.055	-0.097*	-0.072*	-0.062**	-0.027	-0.058***	-0.010	-0.034**	-0.011
	(0.007)	(0.090)	(0.058)	(0.042)	(0.026)	(0.018)	(0.015)	(0.013)	(0.017)	(0.044)
League Position (Home)	0.000	0.000	-0.000	-0.000	-0.000	-0.001**	-0.001	-0.001*	-0.001**	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
League Position (Away)	-0.001***	-0.002**	-0.000	-0.001**	-0.001***	-0.001**	-0.001***	-0.001***	-0.001***	-0.002*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Total Goals Scored (Home)	0.000***	-0.000	0.000*	-0.000	-0.000*	0.000	-0.000	0.000***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Goal Difference (Home)	-0.000*	0.000	-0.000	0.001*	0.000	-0.000*	0.000	-0.000	-0.000***	0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.199***	0.274***	0.281***	0.296***	0.279***	0.213***	0.234***	0.196***	0.202***	0.112***
	(0.004)	(0.053)	(0.037)	(0.027)	(0.017)	(0.012)	(0.011)	(0.009)	(0.011)	(0.032)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626	93,782	17,311
R-squared	0.001	0.003	0.004	0.002	0.002	0.001	0.001	0.001	0.002	0.004
Number of team1id	4,937	70	104	188	325	624	777	1,810	2,788	821
Adjusted R-squared	-0.0115	-0.0111	-0.00827	-0.00994	-0.00989	-0.0100	-0.0115	-0.0167	-0.0288	-0.0472

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 2.22. Outcome Away Win (Clubs with any kind of 3G pitch – for use in competitive matches or for training purposes only)

VARIABLES	(1) All Steps Outcome Away Win	(2) Step 1 Outcome Away Win	(3) Step 2 Outcome Away Win	(4) Step 3 Outcome Away Win	(5) Step 4 Outcome Away Win	(6) Step 5 Outcome Away Win	(7) Step 6 Outcome Away Win	(8) Step 7 Outcome Away Win	(9) Step 8 Outcome Away Win	(10) Step 9 Outcome Away Win
3G Training and match use	0.001	0.050	-0.013	0.001	0.029*	-0.025*	-0.007	0.007	0.017	-0.054
	(0.007)	(0.042)	(0.022)	(0.017)	(0.015)	(0.014)	(0.018)	(0.022)	(0.034)	(0.061)
Elopredict	-0.496***	-0.310***	-0.340***	-0.403***	-0.393***	-0.521***	-0.480***	-0.531***	-0.543***	-0.476***
	(0.008)	(0.094)	(0.061)	(0.046)	(0.029)	(0.022)	(0.019)	(0.016)	(0.020)	(0.054)
League Position (Home)	0.008***	0.001	0.001	0.001	0.004***	0.006***	0.007***	0.007***	0.007***	0.006***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)
League Position (Away)	-0.015***	-0.006***	-0.006***	-0.007***	-0.011***	-0.013***	-0.015***	-0.020***	-0.023***	-0.026***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Total Goals Scored (Home)	0.000**	0.001**	-0.000	0.000	0.000	-0.000**	0.000	0.000	-0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Goal Difference (Home)	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.001***	-0.002***	-0.002***	-0.001***	-0.001***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.688***	0.509***	0.550***	0.631***	0.635***	0.737***	0.718***	0.752***	0.775***	0.834***
	(0.005)	(0.056)	(0.040)	(0.029)	(0.020)	(0.014)	(0.013)	(0.011)	(0.013)	(0.039)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626	93,782	17,311
R-squared	0.091	0.026	0.026	0.038	0.060	0.084	0.099	0.094	0.085	0.075
Number of team1id	4,937	70	104	188	325	624	777	1,810	2,788	821
Adjusted R-squared	0.0797	0.0121	0.0140	0.0264	0.0495	0.0745	0.0880	0.0782	0.0564	0.0280

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 2.28. Outcome Draw (Clubs with 'Match use' 3G pitches only)

VARIABLES	(1) All Steps Outcome Draw	(2) Step 1 Outcome Draw	(3) Step 2 Outcome Draw	(4) Step 3 Outcome Draw	(5) Step 4 Outcome Draw	(6) Step 5 Outcome Draw	(7) Step 6 Outcome Draw	(8) Step 7 Outcome Draw	(9) Step 8 Outcome Draw	(10) Step 9 Outcome Draw
Match Use only Pitch	-0.003	-0.047	0.035*	-0.021	-0.002	0.002	-0.008	0.003	-0.022	0.019
	(0.005)	(0.040)	(0.018)	(0.014)	(0.012)	(0.011)	(0.014)	(0.016)	(0.023)	(0.044)
Elopredict	-0.026***	0.055	-0.097*	-0.072*	-0.062**	-0.027	-0.058***	-0.010	-0.034**	-0.012
	(0.007)	(0.090)	(0.058)	(0.042)	(0.026)	(0.018)	(0.015)	(0.013)	(0.017)	(0.044)
League Position (Home)	0.000	0.000	-0.000	-0.000	-0.000	-0.001**	-0.001	-0.001*	-0.001**	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
League Position (Away)	-0.001***	-0.002**	-0.000	-0.001**	-0.001***	-0.001**	-0.001***	-0.001***	-0.001***	-0.001*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Total Goals Scored (Home)	0.000***	-0.000	0.000*	-0.000	-0.000*	0.000	-0.000	0.000***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Goal Difference (Home)	-0.000*	0.000	-0.000	0.001*	0.000	-0.000*	0.000	-0.000	-0.000***	0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.199***	0.280***	0.280***	0.297***	0.279***	0.213***	0.234***	0.195***	0.202***	0.112***
	(0.004)	(0.054)	(0.037)	(0.027)	(0.017)	(0.012)	(0.011)	(0.009)	(0.011)	(0.032)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626	93,782	17,311
R-squared	0.001	0.003	0.004	0.002	0.002	0.001	0.001	0.001	0.002	0.004
Number of team1id	4,937	70	104	188	325	624	777	1,810	2,788	821
Adjusted R-squared	-0.0115	-0.0111	-0.00842	-0.00992	-0.00992	-0.0100	-0.0115	-0.0167	-0.0288	-0.0472

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 2.29. Outcome Away Win (Clubs with 'Match use' 3G pitches only)

VARIABLES	(1) All Steps Outcome Away Win	(2) Step 1 Outcome Away Win	(3) Step 2 Outcome Away Win	(4) Step 3 Outcome Away Win	(5) Step 4 Outcome Away Win	(6) Step 5 Outcome Away Win	(7) Step 6 Outcome Away Win	(8) Step 7 Outcome Away Win	(9) Step 8 Outcome Away Win	(10) Step 9 Outcome Away Win
Match Use only Pitch	0.001	0.050	-0.011	-0.006	0.032**	-0.027**	-0.000	-0.003	0.022	-0.078
	(0.006)	(0.042)	(0.019)	(0.015)	(0.014)	(0.014)	(0.016)	(0.020)	(0.027)	(0.054)
Elopredict	-0.496***	-0.310***	-0.340***	-0.403***	-0.393***	-0.521***	-0.480***	-0.531***	-0.543***	-0.476***
	(0.008)	(0.094)	(0.061)	(0.046)	(0.029)	(0.022)	(0.019)	(0.016)	(0.020)	(0.054)
League Position (Home)	0.008***	0.001	0.001	0.001	0.004***	0.006***	0.007***	0.007***	0.007***	0.006***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)
League Position (Away)	-0.015***	-0.006***	-0.006***	-0.007***	-0.011***	-0.013***	-0.015***	-0.020***	-0.023***	-0.026***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Total Goals Scored (Home)	0.000**	0.001**	-0.000	0.000	0.000	-0.000**	0.000	0.000	-0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Goal Difference (Home)	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.001***	-0.002***	-0.002***	-0.001***	-0.001***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.688***	0.503***	0.550***	0.632***	0.634***	0.738***	0.717***	0.752***	0.775***	0.834***
	(0.005)	(0.056)	(0.040)	(0.029)	(0.020)	(0.014)	(0.013)	(0.011)	(0.013)	(0.039)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626	93,782	17,311
R-squared	0.091	0.026	0.026	0.038	0.060	0.084	0.099	0.094	0.085	0.075
Number of team1id	4,937	70	104	188	325	624	777	1,810	2,788	821
Adjusted R-squared	0.0797	0.0121	0.0139	0.0264	0.0496	0.0745	0.0880	0.0782	0.0564	0.0281

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 2.35. Outcome Draw with 3G pitches (Both clubs with 3G pitch)

VARIABLES	(1) All Steps Outcome Draw	(2) Step 1 Outcome Draw	(3) Step 2 Outcome Draw	(4) Step 3 Outcome Draw	(5) Step 4 Outcome Draw	(6) Step 5 Outcome Draw	(7) Step 6 Outcome Draw	(8) Step 7 Outcome Draw
Home and Away 3G	-0.008	-0.129**	0.020	-0.017	-0.029	0.002	-0.008	-0.026
	(0.009)	(0.060)	(0.028)	(0.020)	(0.022)	(0.025)	(0.023)	(0.052)
Elopredict	-0.026***	0.050	-0.097*	-0.072*	-0.063**	-0.027	-0.058***	-0.010
	(0.007)	(0.090)	(0.058)	(0.042)	(0.026)	(0.018)	(0.015)	(0.013)
League Position (Home)	0.000	-0.000	-0.000	-0.000	-0.000	-0.001**	-0.001	-0.001*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
League Position (Away)	-0.001***	-0.002**	-0.000	-0.001**	-0.001***	-0.001**	-0.001***	-0.001***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Total Goals Scored (Home)	0.000***	-0.000	0.000*	-0.000	-0.000**	0.000	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Goal Difference (Home)	-0.000*	0.000	-0.000	0.001*	0.000	-0.000*	0.000	-0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.199***	0.277***	0.285***	0.295***	0.279***	0.213***	0.233***	0.196***
	(0.004)	(0.053)	(0.037)	(0.027)	(0.017)	(0.012)	(0.011)	(0.009)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626
R-squared	0.001	0.004	0.003	0.002	0.002	0.001	0.001	0.001
Number of team1id	4,937	70	104	188	325	624	777	1,810
Adjusted R-squared	-0.0115	-0.0105	-0.00876	-0.0100	-0.00986	-0.0100	-0.0115	-0.0167

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday

Table 2.36. Outcome Away Win with 3G pitches (Both clubs with 3G pitch)

VARIABLES	(1) All Steps Outcome Away Win	(2) Step 1 Outcome Away Win	(3) Step 2 Outcome Away Win	(4) Step 3 Outcome Away Win	(5) Step 4 Outcome Away Win	(6) Step 5 Outcome Away Win	(7) Step 6 Outcome Away Win	(8) Step 7 Outcome Away Win
Home and Away 3G	0.011	0.126**	-0.011	-0.002	0.040	-0.027	0.018	0.003
	(0.011)	(0.062)	(0.029)	(0.022)	(0.025)	(0.030)	(0.028)	(0.063)
Elopredict	-0.496***	-0.305***	-0.340***	-0.403***	-0.392***	-0.521***	-0.480***	-0.531***
	(0.008)	(0.094)	(0.061)	(0.046)	(0.029)	(0.022)	(0.019)	(0.016)
League Position (Home)	0.008***	0.001	0.001	0.001	0.004***	0.006***	0.007***	0.007***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
League Position (Away)	-0.015***	-0.006***	-0.006***	-0.007***	-0.011***	-0.013***	-0.015***	-0.020***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Total Goals Scored (Home)	0.000**	0.001**	-0.000	0.000	0.000	-0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Goal Difference (Home)	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.688***	0.506***	0.549***	0.631***	0.636***	0.737***	0.717***	0.752***
	(0.005)	(0.056)	(0.040)	(0.029)	(0.020)	(0.014)	(0.013)	(0.011)
Observations	414,086	6,145	10,015	17,358	29,870	59,855	63,142	105,626
R-squared	0.091	0.026	0.026	0.038	0.060	0.084	0.099	0.094
Number of team1id	4,937	70	104	188	325	624	777	1,810
Adjusted R-squared	0.0797	0.0125	0.0139	0.0264	0.0495	0.0744	0.0880	0.0782

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Fixed effects for Season, Step, Team and Weekday