Banning controversial sponsors: Understanding equilibrium outcomes when sports sponsorships are viewed as two-sided matches*

Yupin Yang

Assistant Professor of Marketing
Beedie School of Business
Simon Fraser University

8888 University Drive
Burnaby, BC, Canada, V5A 1S6
E-mail: yya29@sfu.ca
Tel: 1-778-782-4186
Fax: 1-778-782-4920

Avi Goldfarb

Professor of Marketing
Rotman School of Management
University of Toronto

105 St. George Street
Toronto, ON M5S 3E6, Canada
E-mail: *agoldfarb@rotman.utoronto.ca*
Tel: (416) 946-8604
Fax: (416) 978-5433

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Abstract

This paper applies a two-sided matching model to investigate the consequences of banning controversial sponsors. Using a dataset containing the shirt sponsorships from 43 English football clubs during the period from 1990 to 2010, our estimates suggest assortative matching between a club's attendance and a sponsor's revenue. In addition, sponsorships become less valuable as the distance between the club and the sponsor's head office grows, particularly for worse-performing clubs and smaller domestic sponsors . We use these estimates to simulate the consequences of banning alcohol and gambling sponsors. Our estimates of counterfactual outcomes suggest that such bans may not have the biggest impact on the clubs that currently have alcohol and gambling sponsors, particularly not on the relatively successful ones. Instead, it is clubs with low attendance and clubs in low income areas will be most affected. More generally, the results demonstrate that, when marketing relationships are viewed as the result of a matching process, actions that affect only some marketers may have substantial indirect effects on a variety of players in the market.

1. Introduction

Many marketing decisions are the outcome of a matching process between two or more parties. Retailers decide which manufacturers' products to carry while manufacturers decide which retailers to allow to sell their products. Advertisers decide which media to use and media often decide which advertisers to allow. Sponsors of sports, arts, culture, and charity events decide which organizations to support, and those organizations decide which sponsors to accept. In each case, the match has to be seen as worthwhile to all parties that participate.

In this paper, we use data from 21 years of shirt sponsorships of English football clubs to show that the indirect effects of policy changes in matching markets can be substantial. After estimating a two-sided matching model (Fox 2010), we explore the consequences of banning controversial sponsors such as alcohol and gambling companies. The indirect effects may dominate the direct effects: It is not necessarily the clubs with alcohol and gambling sponsorships that would be most affected by a ban. Many of these clubs will be able to poach sponsors from other clubs. Instead, it is clubs with low attendance and clubs in low income areas that are likely to be most affected, irrespective of whether they were sponsored by a banned sponsor or not.

Shirt sponsorships provide an interesting setting for examining the impact of policy on outcomes in matching markets. The sponsorship of sports, arts, culture, and charity events is a popular promotional tool for organizations of all sizes and across many industries. According to the report of the International Events Group (IEG, 2013), global sponsorship spending reached $51.1 billion in 2012, with the majority of the spending being sports-related. Although sponsorship is a common marketing strategy, we know little about what drives the choices of sponsors and sponsored organizations. Furthermore, sponsorships are a situation where matching matters: Clubs care about which brands sponsor them and sponsors care about which clubs they support.

As an input into our analysis of the impact of banning controversial sponsors, the coefficients of the two-sided matching model suggest, perhaps unsurprisingly, that sponsorships become less valuable as the distance between the club and the sponsor's head office grows. More interestingly, distance is more important for weaker clubs and smaller sponsors. Compared to domestic sponsors, the distance from the UK headquarters of international sponsors to the clubs plays a relatively small role in determining matches. Furthermore, there is assortative matching between a club's performance and a sponsor's financial size.

We use these estimates to simulate the consequences of banning alcohol and gambling sponsorships. In addition to the more general point about the equilibrium impact of policy changes in matching markets, understanding the consequences of sponsorship bans is of interest to both managers and policy-makers. Tobacco sponsorships have been banned from most professional sports in the UK, US, and elsewhere for several years. Recently, attention has turned to banning alcohol and gambling advertisers from sporting events.[1] Our model and estimates demonstrate that such bans will not affect all clubs equally. At the risk of over-simplifying, we believe our results inform policy-makers by suggesting that they shouldn't be surprised if a broad range of constituents are affected by a policy; they inform sponsors by suggesting that such bans might provide an opportunity to reoptimize; and they inform sponsored organizations by suggesting that such bans are likely to lead to substantial reshuffling of matches.

Our study uses a newly constructed dataset that contains 490 shirt sponsorship signings and renewals from 327 sponsors of the 43 English football clubs that appeared in the Premier League at least once during the period from 1979 to 2010. Our policy simulations emphasize 346 shirt sponsorship signings from 1990 to 2010. Shirt sponsorships in English football are an excellent setting to study sponsorships for several reasons. First, there is rich empirical variation with many years of data, many clubs, and many sponsors. Second, English football shirt sponsorships often involve a large amount of money. For example, the Arsenal football club received £30 million in season 2013-2014 from its sponsor

[1] Jones (2010), World Health Organization (2004), and Lamont et al (2011) provide discussions. Examples of news articles are http://www.bbc.com/news/uk-22867315 and http://www.dailymail.co.uk/news/article-438021/Ban-alcohol-ads-say-health-experts-binge-drinking-soars.html (accessed March 31, 2014).

Fly Emirates. Third, there is usually one (and only one) shirt sponsor for each club in each specific year, which allows for better identification of underlying factors. Fourth, shirt sponsorships are a well-established form of sponsorship in English football, meaning we have enough years of data to estimate the parameters. Fifth and finally, there has been some controversy around the prevalence of gambling and (especially) alcohol sponsors in English football, suggesting an interesting policy to study with our counterfactuals.

Unlike the previous literature that often employs manager surveys to study the objectives and selection of sponsorships (Walliser 2003), we apply a two-sided matching model on a dataset containing actual sponsorships to examine these issues. Two-sided matching models are used to study the relationships formed under the mutual agreements of two or more parties (Fox 2010; Yang, Shi & Goldfarb 2009, Wu 2012; Zamudio et al., 2012; Chatain 2013; Mindruta 2013). The formation of sponsorships depends on the mutual agreement of the sponsors and the clubs. Furthermore, within a market, sponsorships are not independent of each other. Rather, who sponsors whom in a market results from the preferences of all the organizations on both sides. The two-sided matching model allows us to examine the interdependence between sponsorships within the same market when both sponsors and clubs need to agree to the partnership.

Our results provide much needed data to discussions of sponsorships and their value. In a particular setting, we document assortative matching in sponsorships. Our analysis is most directly relevant to policy makers interested in regulating sponsorships, suggesting that the impact of a ban is heterogeneous and that the clubs most impacted may not necessarily be the clubs that are sponsored by the gambling and alcohol companies. This calls some current policies into question. For example, Australian states that use tobacco taxes to subsidize organizations that had previously received funds from tobacco sponsorships (Jones 2010) might not allocate the funds to those most affected. Furthermore, at least for English football, our results suggest poorer clubs in poorer locations will be most affected. While equality in sports clubs in hardly a focal issue of welfare analysis, it is relevant to the marketers of such clubs and to local politicians interested in helping lower income areas. Looking forward, policymakers (and industry lobbyists) should consider exactly how a ban will affect their constituents. The equilibrium outcome of matching means that organizations that currently receive funds from a to-be-banned sponsor may not be severely affected by a ban.

More generally, our results provide insight into how the equilibrium outcomes of policy changes in matching markets can be quite different from a naïve look at who is most directly affected. With assortative matching, high value organizations can often identify high quality replacement matches, and it is often lower value organizations that suffer.

The rest of paper is organized as follows. We review the related literature in Section 2, then followed by the industry background and data in Section 3. We describe the two-sided matching model and estimation method in Section 4. The results from the two-sided models are discussed in Section 5. Section 6 describes our counterfactual analysis on banning controversial sponsorships such as alcohol and gambling. We conclude our paper in Section 7.

2. Literature Review and Conceptual Framework

Our conceptual framework draws on the following literatures: sponsorships, strategic alliances, brand alliances, and two-sided matching.

2.1. Research on Sponsorships

To date, academic research on sponsorship has been limited (Walliser, 2003; Cornwell & Maignan 1998). Early research in the area focuses on either defining sponsorship (Meenaghan 1983; Gardner & Shuman 1987; Otker 1988) or on describing the development of sponsorships in a specific industry or country (Gratton & Taylor 1985; Meerabeau et al. 1991). More recent research focused on the managerial aspects of sponsorship, employing surveys to investigate the objectives and motivations underlying sponsorships, finds that enhancing brand image and improving goodwill are the main objectives for sponsorships (Hoek, Gendall &West 1990). Another stream of the literature focuses on measuring the effects of sponsorship on brand awareness and brand attitudes based on consumer surveys

(McDonald, 1991; Speed & Thompson 2000), and field experiments (Pham, 1991). Much of this research emphasizes the 'social' sponsorship of non-profit events and organizations (e.g. Simmons & Becker-Olsen 2006; Becker-Olsen & Hill 2006). Both Speed & Thompson (2000) on sports sponsorships and Simmons & Becker-Olsen (2006) on social sponsorships emphasize the importance of the fit between the sponsor and the sponsorship.

In contrast to this prior work, we focus on revealed preferences of managers in order to understand the processes involved in the formation and renewal of sponsorships. Our study uses data on who sponsored whom and a two-sided matching model to discover the underlying factors influencing the formation of a sponsorship. Using the estimates from the two-sided matching model, we conduct counterfactual analysis to understand how a policy change on sponsorships will impact the parties involved in the market.

2.2. Strategic Alliances

We conceptualize the sponsorship relationship as a strategic alliance. The literature approaches strategic alliances from the point of view of transaction cost theory or the resource-based perspective. Transaction cost theory argues that strategic alliances are formed to provide more efficient organizational mechanisms than other organizational modes such as spot transactions (transactions that complete within a short time frame) and mergers, emphasizing transaction cost (e.g. efficiency) as the motivation for cooperation. This approach has been effective in predicting vertical integration among suppliers and buyers in mature industries such as automobile manufacturing, and the use of equity as a governance mechanism (e.g., Hennart 1988; Osborn & Baughn 1990). Using transaction cost theory, a number of researchers (Shan 1990; Kogut, 1988; Hennart 1991; Teece, 1986) have empirically studied the benefits of strategic alliances (such as cost sharing and reduction; economies of scale and scope; production rationality; and convergence of technologies). The resource-based view (Wernerfelt 1984; Barney 1986, 1991; Peteraf 1993) conceptualizes firms as bundles of resources i.e., in terms of tangible (e.g., financial assets, technology) or intangible (e.g., reputation, managerial skills) strengths or assets of the firm. With respect to strategic alliances, Eisenhardt & Schoonhoven (1996) argue that strategic alliances arise when firms in vulnerable strategic positions (i.e., new markets, many competitors, and pioneering technology) need the resources that alliances bring or when firms in strong social positions (i.e., large, well-connected, and high status top management team) capitalize on their assets to create alliance opportunities. Alliances are, therefore, cooperative relationships driven by a logic of strategic resource needs and social resource opportunities. This perspective emphasizes strategic and social factors, characteristics of the firm (e.g., strategy, top management), and a logic of needs and opportunities.

We suggest that sponsorships are inter-firm cooperation, in which the sponsor needs the intangible resources (i.e. brand image, awareness, customer base and goodwill) of the sponsored organization, while the sponsored organization needs the resources (e.g., financial support) from the sponsors. We therefore argue that the resource-based view explains the formation and renewal of sports sponsorships. Previous empirical work on strategic alliances had studied concurrently formed alliances separately, with the exception of a few recent papers that use the two-sided matching approach (Chatain 2013; Mindruta 2013). Because the interactions between concurrently formed alliances play an important role in the formation of sponsorships, we also use a two-sided matching model to examine the interactions among concurrently formed sponsorships.

Framing sponsorships as strategic alliances also suggests a key variable to study: Distance. The strategic alliance literature is increasingly recognizing that nearby firms are more likely to form alliances (e.g. Sorenson and Stuart 2001) and the role of asymmetric information (e.g. Reuer & Lahiri 2014) in driving the importance of collocation. Our results are consistent with this framing in that sponsors and clubs tend to be geographically proximate, and this proximity is less important for more successful clubs and larger sponsors.

2.3. Brand Alliances

A sponsorship is an association of the sponsoring and the sponsored brands for a certain period of time. Thus, in marketing, sports sponsorships are brand alliances, involving either short- or long-term associations of two or more individual brands, products, and/or other distinctive proprietary assets (Rao &

Ruekert, 1994). In the literature of brand alliances, a majority of the research examines how consumers' attitudes toward a brand are influenced by its allied brand in an experimental setting or through surveys (Venkatesh & Mahajan 1997). For example, Park, Jun & Shocker (1996) study the fit between the two allied brands. Rao, Qu & Ruekert (1999) suggested that a brand ally can be used to signal unobservable product attributes such as durability and reliability; Simonin & Ruth (1998) study the spillover between allied brands and find that less familiar brands experience stronger spillover effects and that the brand fit greatly affects the spillover effect. Van der Lans, van den Bergh, & Dieleman (2014) ask study participants about brand personalities and their ratings of simulated brand alliances. They use structural equation modeling to demonstrate that brands with similar personalities on extrinsic dimensions have higher-rated alliances.

In our previous work, Yang, Shi & Goldfarb (2009), we applied a two-sided matching model to empirically estimate the value created by an alliance between an athlete and a team using the observed contracts between athletes and teams. In the present paper, the signaling effect, spillover effect, or created value through brand alliances between a club and a sponsoring company represent the underlying factors for the formation and renewal of sponsorships. We therefore apply the methodology used in Yang, Shi & Goldfarb (2009) to study the underlying factors of sports sponsorships.

2.4. Two-sided Matching Models

Our empirical approach employs two-sided matching models, which were first used to study the college admission problem (Gale & Shapley 1962). More recently, Fox (2010) has developed an empirical approach to study the supplier-manufacturer relationship. Fox's approach has been applied into relationships such as brand alliances between teams and athletes in professional sports (Yang, Shi & Goldfarb 2009), matching between advertisers and publishers in online advertising (Wu 2012), research collaborations between universities and firms (Mindruta 2013), matching between legal firms and their clients (Chatain 2013), and the job market for Assistant Professors (Zamudio et al. 2012). In two-sided matching models, the market outcomes result from the preferences of agents on both sides. A sports sponsorship is formed based on the mutual agreement between a sponsor and a club or team. Since sponsorships are not formed independently from one another, a two-sided matching approach is appropriate. More generally, given the prior literature, we hope this paper further demonstrates the fruitfulness of the two-sided matching approach to marketing problems beyond sponsorship, including advertising and distribution.

3. Industry Background and Data Description

In this paper, we investigate sponsorships using a dataset containing the 490 shirt sponsorship signings and renewals of 43 English football clubs[2] from 1979 to 2010. Because of missing data in the earlier years, most of our analysis uses data on 346 sponsorships from 1990 to 2010. Unless otherwise stated, we will report results from the later sample. We first provide background information on English Football Leagues and their shirt sponsorships.

3.1. Industry Background

3.1.1. English Football League System and Structure

The English football league system, also known as the football pyramid, is a series of interconnected leagues for men's association football clubs in England, with six additional clubs from Wales and one from Guernsey. The system has a hierarchical format with promotion and relegation between leagues at different levels, allowing even the smallest club the possibility of ultimately rising to the very top of the system. At the top of the system is the single division of the Premier League, which was formed by the 22 top flight clubs from the first division of the Football league in 1992. In 1995, the number of clubs in the Premier League was reduced to 20 clubs to be consistent with the International Federation of Association Football (FIFA). Below the Premier League is the Football League, which is divided into three divisions of 24 clubs each: the Championship (Level 2), League One (Level 3)

[2] Given that English football leagues use the term "club" while other sports leagues such as NBA, NHL, and MLB use the term "team", we use the terms "club" and "team" interchangeably in this paper.

and League Two (Level 4). The 92 clubs in the Premier League and Football League are all full-time professional clubs. Our data include all the 43 English football clubs that appeared at least once in the Premier league from its beginning in 1992 until 2010.

3.1.2 Shirt Sponsorships of Football Clubs

At least as early as 1979, companies started to put their names or logos on the shirts of English football clubs. In most of cases, there is only one sponsor name in the center of football shirts of a club in a season. For a few cases, there are two or more sponsors appeared on a club's shirts in a season.[3] For example, the players of Sheffield United Football Club wore the shirts with VSports in their home games and Top Spring in their away games in 2013-2014 season. As sponsorship deals have become larger and larger, the revenue from shirt sponsorships has become increasingly important for the success of a football club. As reported by sportingintelligence.com (Miller 2013), the combined shirt sponsorship income of the Premier League's 20 clubs was a record £165.75 million in season 2013-2014. The biggest deal in season 2013-2014 is the Arsenal football club's £30 million a year from its sponsor Fly Emirates. Unfortunately, we could not find much detail on the values of most sponsorships, making our matching with transfers model a particularly useful framework for analysis. We collected all the shirt sponsorships of the selected 43 clubs from 1979 to 2010 using the process discussed in the next section.

3.2. Data Description

In this section, we describe how we collected and constructed the sponsorship dataset, the club dataset, and the sponsor dataset. Table 1 summarizes the basic descriptive statistics.

3.2.1. Sponsorship Dataset

We used a variety of sources to collect the shirt sponsorships. First, we used a historical football kits website (http://www.historicalkits.co.uk/) to identify sponsors, clubs, and signing seasons. This website contains images of almost all the shirts of all the English football clubs from 1979 to the present.

[3] In these cases, there is still one corporate sponsor name on the shirt each game.

Aggregate news sources (e.g., LexisNexis) were used to collect whether a sponsorship was renewed and the renewing season. In total, we have 490 sponsorship signings/renewals from 327 sponsors for the 43 clubs from 1979 to 2010 and we focus on the 346 sponsorships from 245 sponsors from 1990 to 2010. We focus on the later data for two reasons. First, as we will discuss below, there is a great deal of missing data prior to 1990. Second, prior to 1990, many clubs did not have sponsors. Starting in 1990, on average 42 of the 43 clubs had sponsors.

For each sponsorship signing/renewal, we include three variables: signing/renewal season, club name, and sponsor name in the sponsorship dataset. Most sponsorships are single-year contracts. For the few sponsorships that are longer contracts, we only include the first year as an observation in our analysis. Sponsorships change often, with the median time that a sponsor stays with the same club of just two years, and 93% of sponsorships last four or fewer years.

3.2.2. Club Dataset

The club dataset includes the following information for each club: stadium address, on-field performance, annual revenue, annual attendance, and demographics of the local authority where the club is located.[4]

We first collect the postcodes of the clubs' stadiums and then convert each postcode to a location with an easting and a northing using the Code-Point of UK Ordnance Survey. Identifying a location with an easting and a northing allows us to use the Pythagorean theorem to calculate the geographical distance between a club's stadium and a sponsor's UK office. Several clubs changed their stadiums over the years, we also collect the addresses of previous stadiums and use the new postcodes of previous stadiums to identify their eastings and northings.

We use three types of measures of club quality: attendance at matches, on-field performance, and annual revenue. Attendance and on-field performance measure are available on the website:

[4] An authority is a local area in the UK, somewhat similar to a county in the United States. There are 326 authorities in England. The 43 clubs in our data are located in 39 different authorities.

http://www.european-football-statistics.co.uk, which contains the data for all the European football clubs since they were first established.

As clubs play at different levels and leagues, it is hard to use the absolute performances such as points to measure the club performance. Instead, we use the relative standings of the clubs among the 92 clubs in the top 4 levels as our performance measure. As a club can be promoted or relegated between leagues at different levels, we also include two dummy variables to indicate whether a club is promoted to or relegated from the Premier League (or the top division before the Premier League was established). As our selected clubs are those that had been to the Premier League, our dummy variables focus on the promotion or relegation of the Premier League or the top division. Not only the performance of the most recent year matters, but also the historical performance matters to sponsors. For example, the "Big Four" clubs, Arsenal, Chelsea, Liverpool, and Manchester United, have dominated the Premier League for many years. Their long appearance in this top league is an important asset of these clubs. Therefore, we include the accumulated percentage in the Premier as another club performance measure.

The annual revenues of clubs are collected through a variety of sources. The main source is ORBIS database. As the ORBIS database provides only the most recent 10 years of financial information, we use other online sources such as the LexisNexis database and newspaper reports. In our data, we have revenue information for 74.6% of the club-years from 1990 to 2010 but just 1 of 321 observations (0.3%) prior to 1990. For missing club-years, we use the numbers from the closest years for the same club to fill in the missing information. General results are robust to alternative ways to address missing data such as linear interpolation. This is unsurprising because the within club variation in revenue is much less than the between club variation in revenue.

The demographics of a club's local authority are collected from the data releases of the Office for National Statistics (ONS), the recognized national statistical institute for the UK. For each club, we include the following variables: the population density of the local authority from 1981 to 2010, weekly earnings index from 1997 to 2010 with the average of England as the base, and industry specialization indices of 2011 at the two-digit code level of the 2007 UK Standard Industrial Classification (SIC) at the local authority. The formula used for the industry concentration index (ICI) is:

$$ICI = \frac{E_{i,r}/E_i}{E_r/E}$$

where $E_{i,r}$ is the number of employee jobs in industry i region r, E_i is the number of employee jobs in industry i, E_r is the number of employee jobs in region r and E is the number of employee jobs in Great Britain. As sponsors are from 54 different SIC codes, we collect the indices for only the related 54 industries at two-digit levels of UK SIC 2007. The industry specialization indices are used to examine whether the sponsors from the highly-concentrated industries are more likely to sponsor their local clubs.

3.2.3 Sponsor Dataset

There are a total of 353 companies that sponsored at least one season of at least one of the 43 clubs during the period 1979-2010. For 26 of these sponsors, we could not find any information about the sponsor and so we dropped them from the data, leaving 327 sponsors with 490 contracts used in the estimation. For the 1990-2010 estimations, we have 250 sponsors and 351 signings and renewals. Just 5 sponsors with no information were dropped from the data leaving 245 sponsors and 346 signings and renewals. For each sponsor, we have information on the UK address (postcode is also converted to a location with an easting and a northing), two-digit UK SIC2007 industry code, annual revenue, and whether a sponsor is an international company whose head office is outside UK.

If a sponsor is based in the UK, the UK address is the company's head office address. If a sponsor is an international company like Samsung, we use its UK address as its head office address. We collect the sponsors' addresses through variety sources such as annual reports if it is a public company, company websites, and business reports from aggregated databases (e.g. LexisNexis and ORBIS). Out of 327 total sponsors, 97 are international companies. Of the 245 sponsors from 1990 to 2010, 78 are international. In both data sets, there are 13 international companies that do not have a UK address or office. For these 13 international companies, we use the longest distance in the data to estimate the distance between a club and these sponsors. These 13 sponsors account for 30 club-year observations out of the total 881 club-years between 1990 and 2010.

The industry codes of sponsors are collected through ORBIS and LexisNexis. For the codes that are not in UK SIC2007, we convert them to UK SIC2007 using the description details provided in the industry classification by comparing with the descriptions in UK SIC2007. In the cases that a sponsor has multiple industry codes, we use its main industry code. Table 2 summarizes the number of sponsors in different industry groups. As shown in Table 2, sponsors are from many different industries while the main sectors are manufacturing, wholesale and retail, information and communication, and financial and insurance. Our simulations below explore the impact of a ban on alcohol and gambling sponsors. Table 2 shows that this implies dropping 17 alcohol sponsors and 14 gambling sponsors. Between 1990 and 2010, the 17 alcohol sponsors appear 94 times (club-years) in the data and the 14 gambling sponsors appear 33 times (club-years).

Total annual revenue for the majority of sponsors was collected through ORBIS, a financial database. As ORBIS covers only the most recent 10 years of financial data, we also searched for earlier data through other sources such as company websites, Edgar online, and LexisNexis. We converted all the currencies to English pounds using the average exchange rates in the corresponding years, and then discounted all the revenue figures using the UK CPI from 1979 to 2010 to control the inflation factors. For those sponsor-years where we do not have revenue data, we use the nearest year's figure. We have no financial information for 48 sponsors in the full data and 31 sponsors in the 1990-2010 data. For these sponsors, we use the lowest value of the other sponsors in the same industry in that year in our data.

3.2.4 Correlations between sponsor and club characteristics

Table 3 shows the correlation matrix between sponsor and club characteristics for the full data set (1979-2010) and for the main data for estimation (1990-2010). The qualitative results of the two correlation matrices are similar, suggesting that our focus on the latter period does not generate a clear direction of bias. Overall, the correlations suggest assortative matching: Higher revenue sponsors match with better-performing, higher revenue clubs in larger higher income locations. Similarly, international sponsors support better-performing, higher revenue clubs in larger higher income locations.

Next, we build a model that allows us to estimate the relative importance of the various factors in matching. We then use these estimates to simulate equilibrium outcomes by a ban on certain types of sponsors to assess the consequences of policy changes.

4. Two-sided Matching Model

Sponsorships are formed based on the mutual choices of football clubs and sponsors and the formation of a club and a sponsor often impacts the decisions of other clubs and sponsors. Therefore, as discussed above, a two-sided matching model (Fox 2010; Yang, Shi & Goldfarb 2009; Mindruta 2013; Chatain 2013; Wu 2012; Zamudio et al. 2012) is appropriate for jointly studying the choices of clubs and sponsors. Drawing on this prior work, we model the observed partner choices as equilibrium outcomes derived from the two-sided matching model based on the values created by a sponsorship to the club and the sponsoring company in a given year. The value generated by a sponsorship is also a measure of the quality of the match between the club and the sponsoring company. The two-sided matching model thereby enables us to investigate the factors underlying the formations of sports sponsorships by examining the co-existence of these factors across clubs and sponsors.

4.1 Local Production Maximization

In this subsection, we define the equilibrium concept used to solve the two-sided matching problem. We use the local production maximization condition developed by Fox (2010) to define equilibrium. Following Fox (2010), we use the economic language of “production” but simply mean the joint value of a club-sponsor match. Fox’s definition accommodates matching models with unobserved endogenous transfers, meaning that the researcher does not need to know how much money changed hands in order to analyze the matching process. Accommodating unobserved transfers is important in this context because 1) the estimated amount of a sponsorship is only announced in the media for high profile sponsorships, and 2) even for these high-profile sponsorships, a number of features in the contracts are often unobserved (e.g., incentives, renewal option, etc.). In addition, this equilibrium concept can allow for local (i.e. non-global) complementarities, which cannot be solved by an assortative matching model (Becker 1973). This equilibrium concept is closely related to pair-wise stability in cooperative game theory. A match is stable if no coalition of agents prefers to deviate and form a new match. Pair-wise stability means that no pair of agents is willing to exchange and form new matches. Similarly, the local production maximization condition means that the total production of any two observed matches should exceed the total production from an exchange of partners. Otherwise, the alternative matches could be formed without disturbing any other matches to make all the agents better off.

Suppose that the matching outcomes are club *a* with sponsor *i*, and club *b* with sponsor *j*. Let *r* be the transfer from a sponsor to a club, let the function $\Delta V(a,i,t)$ be the value that club *a* adds to sponsor *i* (e.g., their brand equity through increased awareness, goodwill, and image) because of their sponsorship in market *t*, and let $\Delta U(a,i,t)$ be the value that sponsor i adds to (or takes away from) club a's value through their sponsorship. Then the payoff functions for the sponsor (denoted by π^S) and the club (denoted by π^C) can be defined as:

$$\pi^S(a,i,t) = \Delta V(a,i,t) - r_{ait} \quad (1)$$

$$\pi^C(a,i,t) = r_{ait} + \Delta U(a,i,t) \quad (2)$$

The sum of payoffs to club *a* and sponsor *i* from their match is the total value that the sponsorship (a, i, *t*) generates to the two individual brands (club *a* and sponsor *i*). We define this value as the production value of the sponsorship as follows:

$$f(a,i,t) = \Delta V(a,i,t) + \Delta U(a,i,t) \quad (3)$$

We define production values for other matches similarly. Then, local production maximization condition can be written as follows:

$$f(a,i,t) + f(b,j,t) \geq f(a,j,t) + f(b,i,t) \quad (4)$$

The local production maximization condition defined by the above inequality means that the sum of production values from two observed matches is greater than the sum of production values if they exchange partners. This condition says the observed matches are socially optimal for a market with two clubs and two sponsors. However, it is important to note that the local production maximization condition is a necessary (but not sufficient) condition for the equilibrium. A more robust condition is a core stability concept, in which no coalitions of agents deviate from the equilibrium. However, the computational cost of computing core stability is much higher than the benefit for estimation (Fox 2010). Therefore, in our context the local production maximization condition is used as the equilibrium concept.

From the local production maximization conditions, we derive a system of inequalities that defines the interaction between a club's characteristics and a sponsor's characteristics. We apply maximum score estimation (Manski 1975) and find production functions that maximize the total number of inequalities that satisfy Equation (4). Therefore, the objective function can be written as:

$$\max_f Q_H(f) = \frac{1}{H}\sum_{t\in H}\{\sum_{\{a,b,i,j\}\in A_t} 1[\ f(a,i,t) + f(b,j,t) \geq f(a,j,t) + f(b,i,t)]\} \quad (5)$$

H is the number of observed markets and A_t is a realized quartet {a,b,i, j} in the observed market t. 1[.] is the indicator function that is equal to 1 when the inequality in the bracket is true. The maximum score estimator will be any function f that maximizes the score function $Q_H(f)$. It is a consistent semi-parametric estimator that makes no assumptions about the distribution of the error terms.

As emphasized by Fox (2010), the maximum score estimator does not suffer from the "curse of dimensionality" involved with integrating over multivariate distributions. In particular, standard maximum likelihood and method of moment estimators require a nested computation of an equilibrium for every realization of error terms. These complex equilibrium computations are nested within an integral over the unobserved error terms in the market, which should be of a dimension equal to the number of potential matches in the market. In our analysis, this would mean calculating integrals of several hundred dimensions. Maximum score estimation eliminates the need to calculate this multi-dimensional integral. Maximum score estimation has the further advantage of allowing situations with multiple equilibria because equilibrium selection rules do not enter the objective function.

In the estimation, we define a market, t, as the clubs and sponsors that sign/renew their sponsorships in the same season. In total, we have used 490 contract signings and renewals from 32 markets during the period 1979-2010. Much of our analysis emphasizes the 346 contract signings and renewals from the period 1990-2010. In each market, a pair is formed by any two clubs signing with two different sponsors (there are only a handful of cases that one sponsor sponsors two clubs in the same season). In the end, we have 3740 pairs used in the estimation with the full sample and 2744 pairs in the estimation using only the later years of the data.

4.2. Production Function Specification

Function $f(a,i,t)$ is the total value generated by sponsorship (a, i, t) at season t to club a and sponsor *i*. We specify the production function as follows:

$$f(a,i,t) = \alpha X_{at} + \beta[X_{at}Y_{it}] + \gamma Y_{it} + \epsilon_{ait} \quad (6)$$

The club-specific term $\alpha \times X_{at}$, and sponsor-specific term $\gamma \times Y_{it}$ are cancelled out in the inequalities. Our estimation focuses on the interaction term $\beta \times [X_{at} \times Y_{it}]$ of the production function, which is denoted as the matching value MV_{ait} between club *a* and sponsor *i* at time *t*. In this paper, we include the following interaction variables (defined below) between a club and a sponsor:

$$\begin{aligned} MV_{ait} = \beta[X_{at}Y_{it}] = {} & \beta_1 D_{ait} + \beta_2 D_{ait} CQM_{at} + \beta_3 D_{ait} FINC_{it} + \beta_4 D_{ait} INTL_i \\ & + \beta_5 D_{ait} INDUSTD_i + \beta_6 CPM_{at} FINC_{it} + \beta_8 ATTN_{at} FINC_{it} + \beta_9 CRV_{at} FINC_{it} \\ & + \beta_7 CPR_{at} FINC_{it} INTL_i + \beta_{10} PSD_{ait} + \beta_{11} INDUSTC_{ait} + \beta_{12} DEMO_{at} FINC_{it} \quad (7) \end{aligned}$$

Distance-related interactions

The geographical distance between club *a*'s stadium address and sponsor *i*'s UK address in season *t*, D_{ait}, is calculated by applying the Pythagorean theorem. The formula is the following:

$$D_{ait} = \sqrt{(e_{at} - e_i)^2 + (n_{at} - n_i)^2} \quad (8)$$

Where e_{at} and n_{at} are the easting and northing of club a's stadium address in season *t* respectively while e_i and n_i are the easting and northing of sponsor i's UK address. If sponsor *i* does not have a UK address, we apply the longest distance observed in the data to estimate it.

To investigate how the impact of the geographical distance varies across different clubs and sponsors, we include the following interaction variables: (1) $D_{ait}CQM_{at}$, is the interaction variable between the geographical distance and three quality measures CQM_{at} of a club: club performance ranking, club attendance, and club revenue. These variables are included to study whether a winning club can extend its geographical reach on its sponsors. (2) $D_{ait}FINC_{it}$ is the interaction variable between the geographical distance and a sponsor's financial size measured by its annual revenue. We include this variable to study whether the value of geographical distance matters less for a larger company. (3) $D_{ait}INTL_i$ is the interaction variable between the geographical distance and a sponsor's international status $INTL_i$. This variable is included to investigate whether the geographical distance matters less for international sponsors. As international sponsors usually have high awareness, they may be less concerned with raising awareness but rather focusing more on building image. (3) $D_{ait}INDUSTD_i$, is the interaction between the geographical distance and a vector of industry dummy variables. These variables are used to study whether the importance of distance depends on the industry characteristics. We include the industry dummies for the following industries: alcohol manufacturer ($Alcohol_i$), car manufacturers (Car_i), airline companies ($Airline_i$), telecommunication companies including internet and wireless providers ($Telcom_i$), and gambling companies ($Gambling_i$). All other companies treated as the baseline with a value of zero.

Interactions between a club's quality and a sponsor's financial size

To investigate the matching between a club's quality and sponsor's financial size, we include the following interaction variables: $CPM_{at}FINC_{it}$, $ATTN_{at}FINC_{it}$, and $CRV_{at}FINC_{it}$. A club's quality is measured by three metrics: on field performance CPM_{at}, club attendance $ATTN_{at}$ and club revenue CRV_{at}. A club's performance CPM_{at} is measured by the following four variables: a club's performance ranking CPR_{at} in season *t*, a dummy variable to indicate whether a club is promoted to the top league PMD_{at} in season *t*, a dummy variable to indicate whether a club is relegated from the top league RLD_{at} in season *t*, and a club's accumulated percentage at the top league APT_{at} from its founding year to season *t*. A sponsor's annual revenue $FINC_{it}$ in season t is used to measure the sponsor's financial size. To examine whether the matching value differs between domestic sponsors and international sponsors, we include the following three-way interaction variables: $CPR_{at}\ FINC_{it}INTL_i$.

Previous sponsorship effect, local industry concentration effect and local demographics effects.

We also include a dummy variable PSD_{ait} to indicate whether club *a* and sponsor *i* had a previous sponsorship before season *t*. This dummy variable is included to study the switching cost or lock-in effect generated by a previous sponsorship. Also, the model includes $INDUSTC_{ait}$, which is the club a's local authority's industry concentration index in sponsor *i*'s industry. This industry code is at 2-digit code of the UK SIC2007. The sponsors used in the estimation come from 54 different 2-digit industry codes. In addition, we include two demographic measures of local authorities— population density and weekly earning index — interacting with a sponsor's financial size. These two interaction variables are used to examine how the demographic characteristics of a club's location impact its ability to attract a larger sponsor.

In the estimation, all the continuous variables are rescaled to 0~1 to make the results more interpretable and comparable (Fox 2010; Yang, Shi & Goldfarb 2009). The parameter of the distance variable is normalized to $\beta_1 = \pm 1$.

5. Estimation Results

Next, we show how the matching value generated by a sponsorship depends on the geographical distance between a club and a sponsor, their previous relationship, the characteristics of a club (i.e., performance, attendance, club revenue, industry concentration and demographics of the local authority) and a sponsor (i.e., financial size, industry, international status). Table 4 includes the parameter estimates for nine different specifications of the two-sided matching model. Numbers in bold are significantly different from zero with at least 95% confidence. The full confidence intervals are shown in appendix Table A1.

Models 1 through 5 use the data from 1990 to 2010 and include different specifications of included covariates. These specifications show the qualitative results are robust to including alternative covariates. In particular, model 1 includes the coefficients that were significantly different from zero in any of the specifications we ran (plus the interaction of distance with alcohol manufacturer because of the simulation on banning alcohol, and the interaction of sponsor revenue with relegated from the top league for symmetry with the inclusion of promotion to the top league). Model 2 does not include attendance or the interaction of distance and company revenue. Model 3 only includes one measure of club performance. Model 4 adds interactions with club revenue. And model 5 drops many club-related interactions.

Model 6 estimates the model using all data from 1979 to 2010. This includes several years with very few sponsorships and several sponsors for which the financial data needed to be interpolated. Model 7 only includes sponsor-year combinations where we could find accurate sponsor revenue data. This restricts the sample substantially.

Models 8 and 9 limit the data to years divisible by 5. While this limits the power of the analysis substantially, it serves as a check against three broad concerns. First, the switching costs may not be well-identified if unobservables are correlated over time. Second, sponsorships can extend for multiple years. Third, autocorrelation in unobservables calls for standard error corrections, which are not readily available for the maximum score estimator used. While autocorrelation may even be an issue every 5 years, we argue that it is more plausible that unobservables at the match level are not correlated across five year gaps. Using data every 5 years allows us to reduce concerns related to switching costs and multi-year sponsorships. For example, less than 7% of sponsorship contracts last five years or more.

The general results are robust across all nine specifications. The maximum scores in the bottom row of Table 4 range from 93.98% to 95.30% for the specifications using the full data set, indicating a very high goodness of fit. The specifications using only years divisible by 5 have maximum scores of

91.76 and 89.80. In our policy simulations, we emphasize the results using all of the 1990 to 2010 data because we believe it hits the right balance between the available financial data and use of the full market in each year. We emphasize model 1 because it encompasses the significant results from the other specifications. In the online appendix, we show simulation results change very little had we used model 3 or model 6. The similarities across specifications in both the estimated coefficients and the policy simulations suggest that the limited financial information for 1979-1989, our consequent interpolation of the revenue values, and our focus on the 1990-2010 period do not drive our results.

5.1. Matching value of geographical distance

As shown in Table 4, the estimated parameter for distance is -1, which suggests that the matching value is higher when a club and a sponsor are geographically closer. This is unsurprising for two reasons: one is related to the resource-based view (Barney 1991) and the other is related to social network perspective of strategic alliance formation (Gulati 1995, 1998) and the role of asymmetric information (Reuer & Lahiri 2014). First, a sponsor's customers, employees, and partners in the geographical areas that are closer to their home base are usually most valuable to the sponsor. Therefore, sponsoring a closer club generates the highest value to the sponsor's stakeholders (customers, employees, partners) as they are more likely to watch and support their local clubs. Second, the manager of a club and the managers of the closer potential sponsors have more shared networking opportunities, which should help to facilitate the formation of a sponsorship.

Perhaps more interestingly, the matching value of geographical distance is generally lower for better performing clubs and for international sponsors. The interaction of distance with club performance is significantly positive in four of nine models and it is never significantly negative. Thus, better-performing clubs are able to attract sponsors from further away.[5] Comparing to coefficients with the

[5] The coefficient on the interaction between distance and performance turns negative and insignificant in Models 4 and 7. For Model 4, we speculate that this is driven by correlation with club revenue. For model 7, we speculate that this is driven by having few small very local sponsors in this data.

(normalized) coefficient on distance of -1, these effects are economically modest: Column 1 suggests moving from the best club to the worst club drives a 1% decrease in distance; Column 3 generates the highest estimate of 19%. Club attendance and club revenue also have positive signs, though the coefficients are not significant in most specifications, perhaps due to collinearity with performance on the field. The interaction of distance with international is always significantly positive. Here distance is defined as distance to the UK headquarters of the company. The magnitudes can be quite large, with model 1 suggesting being that international reduces the effect of distance by 44.5%. The matching value of geographical distance varies on the industries of sponsors. The coefficients for airlines are significantly negative while the ones for telecommunication and gambling sponsors are significantly positive, perhaps because telecommunications and gambling sponsors depend less on geographic location within England for their business.

Given that many of the covariates are correlated, we think column 5 sums up some of the main relationships by using just one measure of club quality (performance) and fewer interactions with sponsor revenue. The results show that distance matters less for better-performing clubs, for larger sponsors, and for international sponsors. We interpret this as evidence that performance (at the club and sponsor level) can overcome the costs of long-distance matches.

Overall, the results on distance suggest that distance matters, but mainly for lower-performing teams and domestic sponsors. International sponsors in particular are much less affected by distance to their UK headquarters than domestic sponsors.

5.2. Assortative matching between clubs and sponsors

Our results show that there is assortative matching between clubs and sponsors. All significant coefficients on the interaction between sponsor revenue and the various measures of club quality are positive. We include several measures of club quality. The attendance results are strongest, with the value positive and significantly different from zero in all the specifications that include the interaction between club attendance and log sponsor revenue. When this interaction is not included (models 2 and 5), the interaction between club on-field performance and log sponsor revenue becomes significant and positive. This suggests that the positive assortative matching is more driven by actual attendance than club performance. Perhaps performance drives attendance, and that is what sponsors care about. The discrete jump of being promoted to the top league also seems to attract sponsors with higher revenues, while being relegated to the league below has a negative sign (as expected) but the coefficients are insignificant and smaller in absolute magnitude. Clubs in higher income areas also attract higher revenue sponsors, as indicated by the positive and significant coefficient on the interaction between the weekly earning index and log sponsor revenue.

The assortative matching suggests a higher matching value between a better clubs and larger sponsors. This helps top flight clubs but may make it difficult for lower ranked clubs with fewer fans to rise up to the top league. This may be a contributing factor to the dominance of "Big Four" clubs—Arsenal, Chelsea, Liverpool and Manchester United—who have dominated the top spots of the league and won 19 out of 21 titles since the Premier League was established in 1992. Clubs with more fans can attract better sponsors, which allows them to hire better players (and be more likely to win and get even more fans).

Further, our results show that the coefficient for the three-way interaction variable, Club performance × sponsor revenue × international sponsor, is significantly positive in all six specifications that include it. This result suggests that the matching value between high performing clubs and international sponsors' financial size is significantly higher. Thus, the assortative matching is particularly strong for international sponsors.

5.3. Lock-in effect or switching cost:

The estimate on the previous sponsorship effect is positive, statistically significant, and economically large in all specifications. This significant positive number suggests that previous sponsorships generate a lock-in effect or switching cost for future sponsorships. As a previous sponsorship creates goodwill and a brand association between a club and a sponsor, the goodwill and brand association can be carried over to future sponsorship if they renew their relationship. It also possible that learning may occur to both the club and the sponsor from previous sponsorship relationship (Doz 1996), creating a disproportionate benefit for sustaining the relationship.

5.4. Industry specialization effect and local demographics effect:

Our results show that there is positive matching between the industry specialization of a club's local authority (city) and a sponsor's industry. This result suggests that more value is generated from a sponsor whose industry is more important for the local area. The reasons could be: a) as more people are employed in the industry, sponsoring a local club improves relations with their (potential) employees and local communities. Thus more good will and better public image are generated to the sponsor. b) A local area is known for or has already been associated with its specialized industry. Because of the well-established association among people between the area and the industry, the brand value generated from a sponsorship is higher for the sponsors in the highly concentrated industries of a local area. While we cannot separate out these two effects, we think it is noteworthy that our results suggest that, even controlling for distance, sponsors choose locations with high same-industry employment.

Our results also show that the matching between local weekly earning index and sponsor's revenue is significant positive across all seven models. This suggests that clubs located in richer areas are more likely to attract a bigger sponsor.

Next, we estimate what happens with advertising and promotion of controversial products when sports sponsorships are banned.

6. Policy Experiments

6.1. Methodology for policy experiments

As discussed above, advertising and promotion of controversial products such as tobacco, alcohol, and gambling are highly regulated in many countries and even banned in some countries. For example, sponsorships of sporting events by tobacco sponsors are banned in UK. However, alcohol sponsors have played a large role in sports sponsorships for some time, and, more recently, gambling sponsors have become important sponsors of clubs. This has led some to call for bans of either or both. Therefore, it is useful for policy makers, clubs, and sponsors to understand the impact of a possible ban on alcohol or gambling on individual clubs and the whole market. In particular, it is important to ask which clubs will be hurt most by the ban and what is the magnitude of the impact on the whole market. In this section, we investigate the impact of a ban on alcohol sponsors, gambling sponsors, or both. Specifically, we look at the 21 years in the data (1990-2010) and ask what the market would have looked like if certain sponsors were prohibited.[6] We do this using the following steps:

Step 1. Define simulated markets. We define a market to be a season with the clubs and their sponsoring sponsors in a season grouped together. In total, 21 simulated markets from season 1990 to 2010[7] are constructed. On average, there are 42 clubs in each simulated market.[8]

Step 2. Calculate matching value matrix. Within each simulated market, the matching values are calculated for all the possible matches between a club and a sponsor using the following formula for the adjusted matching value: $AMV_{ait} = MV_{ait} - C = \beta \times [X_{at} \times Y_{it}] - C$, where term $\beta \times [X_{at} \times Y_{it}]$ is calculated using Equation (7) and the estimates from the two-sided matching model, and C is a constant which is equal to the minimum of all the matching values. The transformation of the matching values by adding a constant term[9] will ensure that the individual rationality condition is satisfied for all the clubs and sponsors in each market. In other words, it would be better for a club or a sponsor to match with a partner than to be unmatched.

[6] Thus, we simulate what the market would have looked like had a ban been in place, rather than predict what will happen next year if a ban is implemented. We do this because it means we do not have to predict out of sample in the time series, we only need to predict out of sample based on the model. This means our results are better seen as a long run estimate of the impact of a ban on different types of clubs. The presence of switching costs means that the short run impact on clubs that currently have alcohol and gambling sponsors is likely to be higher.

[7] As the financial information on earlier years (before 1990) are often estimated, those markets are not included in our simulation.

[8] Some clubs did not have a sponsor in a season. Therefore, the average (42) is lower than the total number of clubs studied in the two-sided matching model (43).

[9] As maximum score estimation will not identify the absolute matching values, any linear transformation of the matching values will result in the same maximum score in Equation (5) (Fox, 2010).

Step 3. Simulate the optimal matches and calculate the optimal matching values. An assignment problem for each simulated market is constructed using the matching value matrix calculated in step 2. The problem is specified as follows:

$$max \sum_a \sum_i d_{ai} \times AMV_{ait}$$

$s.t.\ d_{ai} \in \{0,1\}$,

$\sum_a d_{ai} \leq 1\ \forall\ all\ i\ in\ market\ t,$

$\sum_i d_{ai} \leq 1\ \forall\ all\ a\ in\ market\ t.$

The optimal matches for the problem above are obtained through a linear program (Shapley & Shubik 1971) for each simulated market. The optimal matching value $\widetilde{AMV}_{at}$for each club is obtained for each simulated market based on the solution to the assignment problem. As noted by Roth and Sotomayer (1990), the possible equilibria are different in cooperative and non-cooperative games. In particular, non-cooperative models are likely to give rise to some alternative equilibria that do not maximize the total matching value. As noted by Fox (2010) and others, modeling the match as cooperative game with complete information that maximizes the total matching value is convenient because it leads to a stable and optimal solution.

Step 4. Simulate the counterfactual matches if alcohol sponsorships are banned. Similar to step 3, an assignment problem with the constraints on the alcohol sponsors is solved through linear program to simulate the counterfactual matching outcomes if a ban on alcohol sponsorships is implemented. The assignment problem is described below.

$$max \sum_a \sum_i d_{ai} \times AMV_{ait}$$

$s.t.\ d_{ai} \in \{0,1\}$,

$\sum_i d_{ai} \leq 1\ \forall\ all\ a\ in\ market\ t.$

$\sum_a d_{ai} \leq 1\ \forall\ i\ if\ i\ is\ a\ non-alcohol\ company\ in\ market\ t,$

$\sum_a d_{ai} = 0\ \forall\ i\ if\ i\ is\ an\ alcohol\ company\ in\ market\ t.$

Based on the counterfactual matches, the counterfactual matching value $A\ddot{M}V_{at}$ for each club is calculated for each simulated market. For those clubs without a sponsor in the counterfactual matches, the matching value is assigned to be zero, which is the lowest matching value across all the simulated markets. In other words, clubs without a sponsor get a value equal to the lowest observed match between a club and a sponsor.

Step 5. Calculate the impact of a ban on alcohol sponsorships. The difference between the optimal matching value and the counterfactual matching value is calculated for each club in each simulated markets. That is, $DMV_{at} = \widetilde{AMV}_{at} - A\ddot{M}V_{at}$.

Step 6. Repeat step 4 and step 5 for a ban on gambling sponsorships.

Step 7. Repeat step 4 and step 5 for a ban both alcohol and gambling sponsorships.

6.2.Characteristics of original and optimal matches

In the simulations, 85.58% of the optimal match outcomes (step 4) are the same as the original matches. This result shows a very high goodness of fit of the two-sided matching model. Table 5 shows the close fit of the optimal matches in a different way. It shows the differences in average characteristics between the original matches in the raw data and our simulated estimates of the optimal matches based on our parameter estimates. Comparing across columns 1 and 4, 2 and 5, and 3 and 6 shows that the original and simulated optimal matches are similar.

Table 5 also shows differences between clubs that match with alcohol sponsors, gambling sponsors, and other sponsors. Alcohol and gambling sponsors tend to match with better clubs in terms of current and past performance, revenue, and attendance. These better-performing clubs tend to be in relatively low income locations.

Next, we analyze the impact of a ban on the total market and by club characteristics.

6.3. Impact on the total market

To examine the overall impact of a ban, we calculate the matching value loss denoted as MVL_t for each simulated market using the following formula:

$$MVL_t = \sum_a DMV_{at} \quad (10)$$

The matching value loss measures the total matching value estimated to be lost if a ban is implemented. We calculate the matching value loss for banning alcohol sponsorships, banning gambling sponsorships, and banning both for each simulated market.

Figure 1 shows the matching value loss for each year of banning alcohol sponsors, gambling sponsors, or both. It shows that the impact of banning alcohol sponsors is highest in the 1990s, and the impact of banning gambling sponsors is highest in the 2000s (because there are more alcohol sponsors in the 1990s and gambling sponsors only start appearing in the data in the 2000s).

Table 6 summarizes the average matching value loss and the average number of clubs that are impacted each year. It shows that the impact is spread unevenly across clubs. For those clubs that end up without a matching sponsor, the matching value loss is largest. For the clubs that end up with a different matching sponsor, some gain and others lose, but the impact is much smaller. In all three simulations, over 85% of the loss in match value is driven by those clubs that do not find a new sponsor. Therefore, when we dig into the heterogeneous impact of bans across clubs, we provide detailed comparisons of those clubs that find new sponsors and those that do not.

6.3. Impact on individual clubs

Tables 7, 8, and 9 dig into which clubs were most affected. As suggested by Table 6, it is the clubs that failed to find sponsors after the ban that had the biggest reduction in match values. Table 7 provides further detail into this result. It examines the match value for clubs that had a banned sponsor in the optimal simulation and found a new sponsor with clubs that did not find a new sponsor. It also looks at those clubs that did not have a banned sponsor, but still changed sponsors.

The results reinforce Table 6: It is clubs that ended up without a sponsor that were most hurt. Because we assume that these clubs received a match value equal to the lowest observed match value, this might be considered a lower bound on the impact. This will be a lower bound if we assume that any new sponsors who might come in to sponsor the unmatched clubs are as good as the worst observed sponsor. In other words, these sponsors are likely to be an even worse match because they chose not to sponsor any clubs in the actual data. Of course, alternative assumptions can generate different results and we explore two alternatives below.

Perhaps most striking is the comparison between clubs that had banned sponsors and now have other sponsors, and clubs that did not have banned sponsors and now have no sponsors. Clubs that had banned sponsors but found new ones only experience a slight loss in match value. In contrast, clubs that ended up without a sponsor are much worse off, even if their initial sponsors were not banned. This suggests that the identity of the sponsor is not critical to understanding who is affected. Instead, it must be certain characteristics of the clubs that determine who is most hurt.

Table 8 shows that the simulation suggests better performing clubs and larger wealthier locations are much better at attracting new sponsors. It looks at clubs that had a banned sponsor and compares the counterfactual clubs that found a new sponsor with clubs that did not. Clubs that found a new sponsor performed better on the field, had more revenue and higher attendance, and are located in higher income more densely populated areas.

Table 9 looks at all clubs, regardless of sponsor, and examines what types of clubs are more affected by a ban. It shows the results of regressing the loss in match value on club and location characteristics. The loss is calculated as the difference in match value between the simulated optimum and the counterfactual under a sponsorship ban. A more positive coefficient means that clubs with higher values of that characteristic were estimated to be more hurt by the ban.

While the results vary somewhat for bans of alcohol sponsors, gambling sponsors, or both, there are some consistencies. First, in all specifications, the coefficient on local weekly earning index is negative. This means that clubs in higher income locations are less hurt by a (simulated) ban. Second, in all specifications, the coefficient on club attendance is negative, though it is not significant in the gambling sponsor bans. This suggests that clubs with higher attendance are less hurt by a ban. This is consistent with the results of Tables 6 and 8 which show that clubs with low attendance and clubs in low income areas were more likely to lose their sponsor.

In summary, the impact of a ban is significant in economic value, and is likely to have the biggest impact on clubs in lower income locations with poor attendance numbers. The cost of a ban is not necessarily borne by those clubs currently with alcohol and gambling sponsors. Instead it is borne by those clubs that are unlikely to be able to find a high quality replacement sponsor, regardless of whether their current sponsor is to be banned.

6.4. Alternative assumptions for the counterfactuals

In this subsection, we explore two alternative assumptions for the counterfactuals.

In the main specification, we have assumed that the matching values of unmatched clubs are zero, which is the lowest matching value for a potential sponsorship between a club and a company across all the 21 simulated markets (i.e. all 21 years). However, this assumption does not consider club-specific factors that may influence their outside matching values. To address this concern, we explore an alternative assumption that allows the matching values of unmatched clubs in the counterfactual to differ across the clubs. In the counterfactuals under this alternative assumption, we use the minimum of the values of a club matching with its original sponsors across all the 21 simulated markets as its benchmark matching value if it cannot find a match in the counterfactual. That is, if a club is unmatched in the counterfactual, the club can find a potential sponsor that can provide a matching value that at least as good as the lowest of its observed sponsors across all years. Therefore, if a club is unmatched in the counterfactuals, the matching value loss for a club is now calculated as the difference between its optimal matching value and a club-specific benchmark matching value.

Even though the main assumption and first alternative assumption assume that unmatched clubs can find a potential sponsor with a benchmark matching value either zero or a club-specific term, new potential sponsors do not directly enter the matching problem in the simulations. It is possible that banning alcohol or gambling may generate an influx of new potential sponsors to the market. To address this issue, our second alternative assumption allows all non-alcohol, non-gambling sponsors from the following two years to be the potential sponsors for the current year market in addition to current year sponsors. Under the second alternative assumption, we first calculate the matching value matrix for the clubs matching with the potential sponsors from both the current year and the future two years, and then we simulate the optimal matches and counterfactual matches using the new matching value matrix. The matching value loss for a club is calculated as the difference between the matching value of its optimal matching sponsor and that of its counterfactual matching sponsor. With more sponsors than clubs in a market under the second alternative assumption, every club can find a matching sponsor when there is a ban.

When we calculate the adjusted matching values for the counterfactuals under both main specification and the two new alternative assumptions, we use the same normalization—adding the same constant term to the matching values calculated based on the estimates from the two-sided matching model. Therefore, the results are comparable across years and across different counterfactuals.

Table 10, like Table 6, summarizes the average matching value loss for the clubs with banned sponsors and clubs without banned sponsors under the two alternative assumptions. In contrast to our main specification, it shows that the average matching value losses of the clubs with banned sponsors are higher than that of the clubs without banned sponsors. However, if we look at matching value losses for individual clubs, there are still some clubs without banned sponsors are hurt more than the average of the clubs with banned sponsors. For example, there are 2 such cases under the first alternative assumption and 3 such cases under the second alternative assumption when banning both alcohol and gambling. There are also many cases where the clubs with banned sponsors are hurt less than the average of the clubs without banned sponsors. Under the first alternative assumption, there are 20 such cases when banning both alcohol and gambling while there are 10 such cases under the second alternative assumption. Therefore, our result that the clubs with banned sponsors are not *necessarily* hurt more than the clubs without banned sponsors still holds under the alternative assumptions, though allowing higher value alternative options does mean that on average it is the clubs with banned sponsors that are hurt more.

Similar to Table 9, Table 11 examines which club characteristics influence the impact of a ban on individual clubs under the new alternative assumptions. In general, the results of the main specification are robust to the alternative assumptions. For example, all the coefficients for the local weekly earning index are negative, and 5 out of 6 coefficients are significant. This result is consistent with our main specification, which indicates those clubs located in lower income areas are hurt more. The coefficients on Club Performance and Revenue are also of similar sign and magnitude.

In general, we interpret the results of these alternative counterfactuals to suggest robustness of the core conclusions of our main specification, though the magnitude of the results is smaller.

6.5. Counterfactuals without switching cost

In this subsection, we examine counterfactuals using only the data from years divisible by 5. The purpose of this exercise is to assess the importance of switching costs, autocorrelation, and multi-year contracts on our counterfactual results. As discussed in Section 5, we argue that it is plausible that unobservables at the match level are not correlated across 5 year gaps. Using data every 5 years allows us to reduce concerns from switching costs and multi-year sponsorships.

To conduct the counterfactuals without switching costs, we first estimate the parameters for a two-sided matching model that is the same as Model 1 except that the parameters don't include the previous sponsorship variable using data containing only 1990, 1995, 2000, 2005, and 2010 (as shown in Table 4 column 8). After obtaining the estimates, we follow the similar procedure for the counterfactuals described in subsection 6.1 and 6.4. We calculate the adjusted matching value matrix by adding the same constant term as previous counterfactuals, and then solve the matching problems for the optimal matches and counterfactual matches for only 5 simulated markets (1990, 1995, 2000, 2005, 2010). Similar to the counterfactuals shown above, the matching value benchmark for those unmatched clubs in this exercise is the minimum of all the matching values of a potential sponsor matching with a club across 5 markets under the main specification, a team-specific term—the minimum of matching values of a club matching with its 5 observed sponsors under the first alternative assumption on the counterfactuals, and allowing additional sponsors from future years under the second alternative assumption.

Tables 12 and 13 summarize the results of the counterfactuals without switching costs. Table 12 shows that the average impact of the clubs without banned sponsors is similar to the average impact of the clubs with banned sponsors under the main specification. The results under the two alternative counterfactual models also reflect the main specification: it is not necessarily those with banned sponsors that are affected most. In fact, under the second alternative assumption which allows additional sponsors from future years, the average impact of the clubs without banned sponsors is even higher than that of the clubs with banned sponsors. Thus, unlike the results of the alternative simulations using the full data set shown in Table 10, our main conclusions are not weaker and on average clubs with banned sponsors are not worse off.

Table 13 replicates the analysis of Table 9 that correlates the impact of a ban with club characteristics. With substantially less data, the results are noisier with fewer significant coefficients. Again it is clubs in places with weak local economies that are hurt most: the coefficients of the local weekly earning index variables are still negative under the main specification and first alternative assumption. In contrast the correlations of the impact of the ban and club performance and outcome measures are less clearly consistent with Table 9 in that the signs sometimes reverse, and most results do not give 90% confidence.

Overall, however, we interpret Tables 12 and 13 to suggest that our main conclusions—that clubs with banned sponsors are not necessarily hurt most and instead it is clubs in low income areas that are hurt most—are robust to the problems arising from switching costs, autocorrelation, and multi-year contracts.

7. Conclusion

This paper applies a two-sided matching model to study the underlying factors that influence the formation of sport sponsorships. We find that geographical distance is an important factor even for sports sponsorships, which are alliances that mainly involve money transfers and intangible assets. However, geographical distance appears to be less costly for better-performing clubs and for larger and/or international sponsors. These clubs and sponsors appear able to overcome many of the costs of long-distance matches. Furthermore, there is assortative matching between club quality and sponsor revenue. Because sponsorships are a key revenue source, assortative matching exacerbates differences between clubs and consequently may be a contributor to the persistent dominance of few big clubs in the football league.

Studying sports sponsorships using two-sided matching models allows us to examine the interdependence among sponsorship decisions. Our counterfactual experiments demonstrate that capturing this interdependence is particularly important to understanding the impact of a policy change in a matching market such as a ban on potentially controversial sponsorships. We estimate that about £24 million, or 14% of the total matching value, will be lost if a ban on alcohol and gambling sponsorships is implemented.

It is not necessarily the clubs with alcohol and gambling sponsors that are most affected. Many of them are able to poach replacement sponsors from other clubs. Because these sponsors tend to come from worse-performing clubs in relatively low income areas, it is these clubs that are most negatively affected by a ban. To be clear, the result that it is worse performing clubs that are most affected may be specific to our application: it depends on the empirical distribution of clubs and sponsors. In contrast, the result that the indirect effects matter is a general point about equilibrium in matching models. As Edelman & Schwarz (2010) showed in their examination of reserve prices in sponsored search auctions, in a matching setting, the indirect impact of a blunt policy can be larger than the direct impact. In considering the consequences of a change in government policy or competitor behavior, our results suggest the value in viewing market outcomes as matches and then thinking through the equilibrium.

More generally, our results highlight the usefulness of two-sided matching models to a variety of marketing contexts in which outcomes depend on the mutual agreement of two or more parties. We believe this paper has demonstrated the usefulness of two-sided matching models as tools for understanding the indirect consequences of management and policy decisions in such markets.

As with any empirical paper, our analysis suffers from some limitations that may form a basis for future research. First, our model does not incorporate forward-looking behavior of either clubs or sponsors. The equilibrium could change if the sponsors or clubs anticipate switching costs. Second, and related, our simulations do not take the current sponsorships as given and them simulate what is likely to happen next year. Instead, we simulate what the market would have looked like had a ban been in place. This means that our results are better seen as a long-run estimate of the impact of a ban on different types of clubs. The presence of switching costs means that the short-term impact of a ban is likely to increase the relative importance of the direct effect. Third, our main specification assumes that the value of any new sponsors is equivalent to the lowest matching value. While we view this as a conservative assumption in terms of the overall size of the loss in match value and we explore robustness to alternative assumptions, our results are constrained by the validity of our chosen assumptions. Fourth, we model the matching decisions as a cooperative game with a particular structure. To the extent our assumptions deviate from the true matching process, our results may be inaccurate. For example, we model matches as a cooperative game that maximizes total surplus. Alternative models, perhaps drawing on non-cooperative game theory and incomplete information, might yield different equilibria. Fifth and finally, our empirical analysis focuses on one particular sponsorship setting. While English football is a relatively large sponsorship market, it is not clear the extent to which our results generalize to other settings, beyond the insight that the indirect effect of a ban can exceed the direct effect.

Notwithstanding these limitations, we believe our results provide an improved understanding of the drivers of sports sponsorships and the potentially surprising consequences of proposed bans on certain types of sponsors. More generally, we have shown that the indirect effects of a policy in a matching market can have large consequences on market outcomes.

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Table 1: Basic Statistics Summary of the Variables in the Data

Variable	Mean	Std. Dev.	Min	Max
Full Sample 1979-2010				
No. of observations (club-years)	1202			
Club side				
Club performance ranking (normalized)	0.71	0.21	0.00	1.00
Promoted to the top league/division	0.06	0.24	0.00	1.00
Relegated from the top league/division	0.06	0.24	0.00	1.00
Accumulated percentage at the top league/division	0.50	0.27	0.00	0.96
Club revenue (in million pounds)	21.58	31.52	0.46	286.42
Club attendance (‘000)	20.38	11.95	1.75	75.83
Population density (number of persons per hectare)	36.37	23.53	6.59	111.31
Local weekly earnings index	0.98	0.15	0.80	1.38
Industry concentration indices#	0.89	1.20	0.00	19.39
Sponsor side				
Sponsor revenue (in million pounds)	3868.70	10200.00	1.00	124000.00
International sponsor dummy	0.34	0.47	0.00	1.00
Sponsorship length (N=490)	2.62	1.55	1.00	15
Estimation Sample 1990-2010				
No. of observations (club-years)	881			
Club side				
Club performance ranking (normalized)	0.72	0.20	0.00	1.00
Promoted to the top league/division	0.07	0.25	0.00	1.00
Relegated from the top league/division	0.07	0.25	0.00	1.00
Accumulated percentage at the top league/division	0.50	0.27	0.00	0.96
Club revenue (in million pounds)	26.10	35.57	0.46	286.42
Club attendance (‘000)	22.03	12.30	1.75	75.83
Population density (number of persons per hectare)	37.02	26.07	6.63	130.62
Local weekly earnings index	0.98	0.15	0.75	1.75
Industry concentration indices#	0.89	1.21	0.00	19.39
Sponsor side				
Sponsor revenue (in million pounds)	3921.40	10800.00	1.00	124000.00
International sponsor dummy	0.35	0.48	0.00	1.00
Sponsorship length (N=346)	2.51	1.42	1.00	15.00

Based on the values across 54 industries

Table 2: Summary of Sponsors' Industries

Industry Category*	# of Sponsors 1979-2010	# of Sponsors 1990-2010	UK SIC2007 Code
MANUFACTURING	**120**	**81**	
Manufacturers of Food Products	11	10	10
Manufacturers of Alcohol	30	17	11
Manufacturer of electronics, computers, communication equipment components or accessories, telephones, GPS, appliances, electrical products, printers.	42	31	26, 27,28
Manufacturers of automobiles, or train, aircraft, parts	8	4	29, 30
Manufacturers of other goods	29	19	13-25,31,32
ELECTRICITY, GAS, STEAM & AIR CONDITIONING SUPPLY	**3**	**3**	35
WATER SUPPLY; SEWERAGE, WASTE MANAGEMENT & REMEDIATION ACTIVITIES	**0**	**0**	38
CONSTRUCTION	**12**	**8**	41, 43
WHOLESALE AND RETAIL TRADE; REPAIR OF MOTOR VEHICLES & MOTORCYCLES	**57**	**42**	45, 46, 47
TRANSPORTATION & STORAGE	**15**	**8**	
Airlines (Air transport)	9	6	51
Warehousing and support activities for transportation, Postal and courier activities	6	2	52, 53
ACCOMMODATION & FOOD SERVICE ACTIVITIES	**6**	**4**	55, 56
INFORMATION & COMMUNICATION	**40**	**35**	
Publishing activities (e.g., newspapers, magazines)	14	11	58
Programming and broadcasting activities (e.g., Radio stations)	5	3	60
Telecommunications (e.g., Internet, wireless, satellite)	11	11	61
Computer programming, consultancy and related activities	10	10	62
FINANCIAL & INSURANCE ACTIVITIES	**36**	**31**	64, 65, 66
REAL ESTATE ACTIVITIES	**2**	**2**	68
PROFESSIONAL, SCIENTIFIC & TECHNICAL ACTIVITIES	**3**	**3**	69-75
ADMINISTRATIVE & SUPPORT SERVICE ACTIVITIES (e.g., travel agencies)	**7**	**6**	78, 79
PUBLIC ADMINISTRATION & DEFENCE; COMPULSORY SOCIAL SECURITY	**3**	**1**	84
EDUCATION, HUMAN HEALTH & SOCIAL WORK ACTIVITIES	**3**	**3**	85-88
ARTS, ENTERTAINMENT & RECREATION	**18**	**16**	
Gambling and betting activities	15	14	92
Sports activities and amusement and recreation activities	3	2	93
OTHER SERVICE ACTIVITIES	**2**	**2**	94, 96
TOTAL	**327**	**245**	

The categories are based on the UK Standard Industrial Classification 2007

Table 3: Correlation Matrix

Correlation	Log sponsor revenue	International sponsor	Club performance ranking+	Promoted to the top league	Relegated from the top league	Accumulated percentage at the top league	Log club revenue	Log club attendance	Population density
All data (1979-2010)									
Log sponsor revenue	1.00								
International sponsor	**0.45**	1.00							
Club performance ranking+	**0.35**	**0.36**	1.00						
Promoted to the top league	0.05	-0.02	0.04	1.00					
Relegated from the top league	0.02	-0.02	**0.09**	**-0.07**	1.00				
Accumulated % at the top league	**0.31**	**0.34**	**0.54**	-0.02	0.03	1.00			
Log club revenue	**0.29**	**0.28**	**0.67**	-0.02	**0.08**	**0.55**	1.00		
Log club attendance	**0.35**	**0.35**	**0.77**	0.03	**0.09**	**0.69**	**0.84**	1.00	
Population density(people/hectare)	**0.14**	**0.29**	**0.30**	-0.04	-0.04	**0.23**	**0.22**	**0.23**	1.00
Local weekly earning index	**0.12**	**0.22**	**0.18**	-0.04	-0.05	-0.03	**0.14**	**0.09**	**0.81**
Estimation data (1990-2010)									
Log sponsor revenue	1.00								
International sponsor	**0.43**	1.00							
Club performance ranking+	**0.36**	**0.35**	1.00						
Promoted to the top league	0.02	-0.04	0.04	1.00					
Relegated from the top league	0.02	-0.03	**0.09**	**-0.07**	1.00				
Accumulated % at the top league	**0.31**	**0.36**	**0.60**	-0.02	-0.01	1.00			
Log club revenue	**0.32**	**0.32**	**0.74**	-0.05	**0.08**	**0.58**	1.00		
Log club attendance	**0.35**	**0.32**	**0.79**	0.02	**0.09**	**0.74**	**0.87**		
Population density(people/hectare)	**0.11**	**0.25**	**0.28**	-0.06	-0.05	**0.22**	**0.25**	**0.09**	1.00
Local weekly earning index	**0.14**	**0.19**	**0.18**	**-0.08**	-0.05	0.03	**0.15**	**0.22**	**0.82**

Numbers in bold are significant at the 95% confidence level

+ Values are normalized to a scale from 0 to 1 with 1 as highest

Table 4: Two-sided Matching Model Results

	Data from 1990-2010 (inclusive)					1979-2010 data	Non-missing data	Only years divisible by 5	
Interaction Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Distance-related interactions									
Distance	-1	-1	-1	-1	-1	-1	-1	-1	-1
Distance×club performance ranking	0.011	**0.096**	**0.196**	-0.371	**0.076**	0.003	-0.443	0.099	**0.235**
Distance×log club attendance	0.139		**0.258**	0.237		0.012	0.430	0.236	
Distance×log club revenue				0.586					
Distance×log sponsor revenue	0.068		0.033	0.094	**0.289**	0.197	-0.198	**-2.616**	0.438
Distance×international sponsor dummy	**0.445**	**0.465**	**0.118**	**0.217**	**0.081**	**0.161**	**0.649**	**1.139**	**0.085**
Distance×industry dummies of a sponsor									
Distance×alcohol manufacturer sponsor	-0.582	-0.183	-0.027	-0.037	-0.097	**-0.664**	**-2.168**	**1.263**	**0.200**
Distance×car manufacturer sponsor	-12.819	-2.126	-0.087	-6.040	-2.714	**-0.270**	0.219	0.925	-1.067
Distance×airline sponsor	**-0.530**	**-0.201**	**-0.059**	**-0.245**	-0.369	**-0.582**	-0.211	**1.521**	0.248
Distance×telecommunication sponsor	**0.748**	**0.700**	**0.454**	**0.359**	**0.422**	**0.377**	**0.999**	**2.850**	**0.497**
Distance×gambling sponsor	**0.701**	**0.533**	**0.359**	0.351	**0.627**	**0.423**	**0.986**	-0.478	**0.422**
Club's performance × log sponsor revenue									
Club performance ranking×log sponsor revenue	-0.468	**0.277**	-0.343	**-0.434**	**0.643**	-0.332	**0.359**	-0.479	**0.329**
Promoted to the top league×log sponsor revenue	**0.100**	**0.059**		**0.192**		**0.100**	**0.035**	**-0.296**	
Relegated from the top league×log sponsor revenue	-0.031	-0.072		-0.051		-0.057	-0.408	**-0.418**	
Accumulated % at the top league×log sponsor revenue	0.164	**0.251**		0.014		**0.144**	-0.515	0.225	
Log club attendance × log sponsor revenue	**1.185**		**1.095**	**0.632**		**0.940**	**1.395**	**2.638**	
Log club revenue × log sponsor revenue				0.502					
Club perf. ranking×log sponsor revenue×int'l sponsor	**0.406**	**0.301**		**0.362**		**0.203**	**0.411**	**0.504**	
Previous sponsorship effect	**2.479**	**2.799**	**4.729**	**2.903**	**1.753**	**1.776**	**2.137**		
Local industry concentration effect	**0.521**	**0.583**	**0.411**	**0.486**	**0.554**	**0.385**	**0.729**	**0.253**	-0.036
Club city's population density×log sponsor revenue	-0.170	-0.351	**-0.179**	**-0.480**	-0.458	-0.427	0.036	-0.005	0.130
Club city's weekly earning index×log sponsor revenue	**0.293**	**0.655**	**0.226**	**0.524**	**0.768**	**0.450**	**0.388**	-0.563	0.124
Maximum Score	95.30%	94.93%	95.08%	95.15%	94.42%	93.98%	94.92%	91.76%	89.80%
# of inequalities	2744	2744	2744	2744	2744	3740	945	716	716

Numbers in bold are significant at the 95% confidence level. Confidence intervals shown in Appendix Table A1

Table 5: Differences between clubs sponsored by alcohol, gambling, and other sponsors

Variables	Original matches			Optimal Matches		
	Clubs with alcohol	Clubs with gambling	Clubs with neither alcohol nor gambling	Clubs with alcohol	Clubs with gambling	Clubs with neither alcohol nor gambling
#of observations	94	33	754	94	33	754
Club performance						
Current year	**0.81**	**0.81**	0.70	**0.81**	**0.79**	0.70
	(0.16)	(0.13)	(0.21)	(0.16)	(0.15)	(0.21)
Accumulated percentage	**0.72**	**0.58**	0.47	**0.71**	0.55	0.48
	(0.16)	(0.23)	(0.26)	(0.17)	(0.23)	(0.27)
Club revenue	**32784.27**	**51448.52**	24187.15	**31930.73**	**51475.21**	24292.39
	(35752.69)	(26697.91)	(35389.49)	(35910.32)	(34479.37)	(35106.36)
Club attendance	**27.76**	**28.45**	21.03	**27.03**	**28.30**	21.13
	(10.64)	(7.34)	(12.40)	(10.64)	(10.62)	(12.35)
Population density	33.66	36.61	37.46	33.72	32.52	37.63
	(19.40)	(25.09)	(26.82)	(18.17)	(19.55)	(27.10)
Local weekly earning index	**0.93**	**0.91**	0.98	**0.93**	**0.89**	0.98
	(0.10)	(0.12)	(0.16)	(0.09)	(0.09)	(0.16)

Standard deviation in parentheses. N=881. Unit of observation is the club-year. Data includes 1990-2010. Numbers in bold mean that the alcohol or gambling group is significantly different from the group with neither at the 95% confidence level. Simulations based on Table 4 column (1).

Table 6: The Impact of a Ban in the Whole Market*

	Banning Alcohol		Banning Gambling		Banning Both	
	Matching Value Loss	# of Clubs Impacted	Matching Value Loss	# of Clubs Impacted	Matching Value Loss	# of Clubs Impacted
Clubs without a match	32.59	4.48	10.82	1.57	43.94	6.05
Clubs with a worse match	5.23	3.43	1.65	1.00	6.33	3.81
Clubs with a better match	-0.17	0.52	-0.16	0.14	-0.24	0.48
Total	37.66	8.43	12.31	2.71	50.03	10.33

Numbers are per year averages (i.e. the values are for each market separately).
N=881. Unit of observation is the club-year. Data includes 1990-2010. Simulations based on Table 4 column (1).

Table 7: Impact of a ban depending on the matching outcome

	Banning Alcohol				Banning Gambling				Banning Both			
Club Type	# obs.	Optimal match	Counter-factual match	Diff-erence	# obs.	Optimal match	Counter-factual match	Diff-erence	# obs.	Optimal match	Counter-factual match	Diff-erence
Clubs that had banned sponsors and now have other sponsors	55	**8.52** (1.01)	**6.69** (0.56)	**1.83** (1.05)	13	**8.80** (0.91)	**6.55** (0.36)	**2.25** (1.08)	63	**8.58** (0.99)	**6.66** (0.54)	**1.92** (1.08)
Clubs that had banned sponsors and now have no sponsors	39	**8.55** (0.94)	**0** (0.00)	**8.55** (0.94)	20	**7.30** (1.21)	**0** (0.00)	**7.30** (1.21)	64	**8.16** (1.18)	**0** (0.00)	**8.16** (1.18)
Clubs that did not have banned sponsors and now have other sponsors	28	**6.63** (0.31)	**6.42** (0.30)	**0.21** (0.37)	11	6.84 (0.88)	6.66 (0.98)	0.18 (1.29)	27	6.79 (0.58)	6.53 (0.65)	0.27 (0.82)
Clubs that did not have banned sponsors and now have no sponsors	55	**6.38** (0.38)	**0** (0.00)	**6.38** (0.38)	13	**6.26** (0.20)	**0** (0.00)	**6.26** (0.20)	63	**6.36** (0.36)	**0** (0.00)	**6.36** (0.36)

Standard deviation in parentheses. Unit of observation is the club-year. Data includes 1990-2010. Numbers in bold mean that the optimal and counterfactual groups are significantly different at the 95% confidence level. Simulations based on Table 4 column (1).

Table 8: Comparing clubs with and without a replacing sponsor in the counterfactual matches

	Banning Alcohol		**Banning Gambling**		**Banning Both**	
Variables	Clubs with a replacement	Clubs without a replacement	Clubs with a replacement	Clubs without a replacement	Clubs with a replacement	Clubs without a replacement
#of obs.	55	39	13	20	63	64
Club Performance						
Current year	**0.86**	**0.74**	0.83	0.77	**0.86**	**0.76**
	(0.14)	(0.16)	(0.16)	(0.14)	(0.15)	(0.15)
Accumulated percentage	**0.77**	**0.63**	**0.72**	**0.44**	**0.75**	**0.59**
	(0.13)	(0.18)	(0.10)	(0.22)	(0.12)	(0.22)
Club Revenue	**43751.47**	**15260.46**	**73627.31**	**37076.35**	**48936.37**	**25268.44**
	(41568.90)	(14595.02)	(42620.32)	(17348.93)	(44309.16)	(21003.34)
Club attendance	**31.41**	**20.85**	**36.27**	**23.12**	**32.44**	**22.36**
	(9.40)	(9.19)	(11.99)	(5.23)	(10.25)	(8.39)
Local weekly earning index	**0.96**	**0.89**	**0.94**	**0.85**	**0.96**	**0.88**
	(0.10)	(0.05)	(0.10)	(0.06)	(0.10)	(0.06)
Population Density	**39.58**	**25.46**	**42.00**	**26.37**	**40.64**	**26.30**
	(20.42)	(9.80)	(26.39)	(10.12)	(21.99)	(10.13)

Standard deviation in parentheses. Unit of observation is the club-year. N=881. Data includes 1990-2010. Numbers in bold mean that the with and without replacement groups are significantly different at the 95% confidence level. Simulations based on Table 4 column (1).

Table 9: Summary of the Impact of a Ban on Individual Clubs

Independent Variable	The Impact of Banning					
	Alcohol	**Gambling**	**Both**	**Alcohol**	**Gambling**	**Both**
Constant	4.473***	-0.888*	3.079***	4.463***	-0.179	3.748***
	(0.837)	(0.487)	(0.947)	(1.037)	(0.603)	(1.174)
Club Performance						
Current year	1.728***	-0.631*	0.877	1.728***	-0.648*	0.862
	(0.630)	(0.367)	(0.713)	(0.630)	(0.366)	(0.713)
Accumulated percentage	1.397***	-0.725***	1.087**	1.399***	-0.850***	0.969*
	(0.431)	(0.251)	(0.488)	(0.445)	(0.258)	(0.503)
Log club revenue	-0.104	0.405***	0.291*	-0.104	0.394***	0.281*
	(0.137)	(0.080)	(0.155)	(0.137)	(0.080)	(0.155)
Log club attendance	-0.795**	-0.149	-0.940***	-0.795**	-0.126	-0.919**
	(0.323)	(0.188)	(0.366)	(0.324)	(0.188)	(0.367)
Local weekly earning index	-2.256***	-1.457***	-3.157***	-2.244**	-2.316***	-3.967***
	(0.505)	(0.294)	(0.572)	(0.897)	(0.521)	(1.015)
Population Density				0.000	0.006**	0.006
				(0.005)	(0.003)	(0.006)
R-squared	0.044	0.067	0.042	0.044	0.071	0.043

**significant at the 1% level; ** significant at the 5% level; *significant at the 10% level
Dependent variable is the loss in match value in the counterfactual relative to the simulated optimum. Standard error in parentheses.
N=881. Unit of observation is the club-year. Data includes 1990-2010.Simulations based on Table 4 column (1).

Table 10: Impact of a ban by matching outcome under alternative assumptions on counterfactual matching

	Counterfactual matches based on a team-specific benchmark drawn from all years of data			Counterfactual matches based on all sponsors in the current year and the following two years of data (2009 and 2011 for the 2010 data)		
Club Type	**Alcohol**	**Gambling**	**Both**	**Alcohol**	**Gambling**	**Both**
Clubs that had banned sponsors and now have other sponsors	**1.83** (1.05)	**2.25** (1.08)	**1.92** (1.08)	**2.04** (0.69)	**1.49** (1.20)	**1.91** (0.89)
Clubs that had banned sponsors and now have no sponsors	**2.31** (0.86)	**1.28** (1.16)	**2.00** (1.09)	N/A	N/A	N/A
Clubs that did not have banned sponsors and now have other sponsors	**0.21** (0.37)	0.18 (1.29)	0.27 (0.82)	**0.17** (0.41)	0.16 (1.22)	0.17 (0.93)
Clubs that did not have banned sponsors and now have no sponsors	**0.39** (0.41)	**0.23** (0.38)	**0.36** (0.40)	N/A	N/A	N/A

Standard deviation in parentheses. Unit of observation is the club-year. Data includes 1990-2010. Simulations based on Table 4 column (1). Numbers in bold mean that the difference between the optimal and counterfactual groups is significant at the 95% confidence level

Table 11: Impact of a ban on individual clubs under alternative assumptions on counterfactual matching

	Counterfactual matches based on a team-specific benchmark drawn from all years of data			Counterfactual matches based on all sponsors in the current year and the following two years of data (2009 and 2011 for the 2010 data)		
	Alcohol	**Gambling**	**Both**	**Alcohol**	**Gambling**	**Both**
Constant	0.808***	-0.167	0.568	0.708**	-0.281	0.457
	(0.315)	(0.187)	(0.360)	(0.285)	(0.180)	(0.334)
Club Performance						
Current year	0.492***	-0.085	0.376*	0.360**	-0.162	0.232
	(0.191)	(0.114)	(0.218)	(0.173)	(0.109)	(0.203)
Accumulated percentage	0.721***	-0.150*	0.603***	0.706***	-0.084	0.581***
	(0.135)	(0.080)	(0.154)	(0.122)	(0.077)	(0.143)
Log club revenue	-0.066	0.110***	0.045	-0.070*	0.093***	0.033
	(0.042)	(0.025)	(0.047)	(0.038)	(0.024)	(0.044)
Log club attendance	-0.060	-0.048	-0.111	-0.073	-0.040	-0.122
	(0.098)	(0.058)	(0.112)	(0.089)	(0.056)	(0.104)
Local weekly earning index	-0.490*	-0.637***	-1.039***	-0.209	-0.313**	-0.664**
	(0.273)	(0.162)	(0.311)	(0.247)	(0.155)	(0.289)
Population Density	0.000	0.002**	0.002	-0.001	0.001	0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
R-squared	0.082	0.054	0.079	0.070	0.031	0.055

**significant at the 1% level; ** significant at the 5% level; *significant at the 10% level

Dependent variable is the loss in match value in the counterfactual relative to the simulated optimum. Standard error in parentheses. N=881. Unit of observation is the club-year. Data includes 1990-2010. Simulations based on Table 4 column (1).

Table 12: Impact of a ban by matching outcome in model without switching costs

	Main specification: Counterfactual matches based on all sponsors in the current year			Counterfactual matches based on a team-specific benchmark drawn from all years of data			Counterfactual matches based on all sponsors in the current year and the following two years of data (2009 and 2011 for the 2010 data)		
Club Type	**Alcohol**	**Gambling**	**Both**	**Alcohol**	**Gambling**	**Both**	**Alcohol**	**Gambling**	**Both**
Clubs that had banned sponsors and now have other sponsors	0.29	-0.51	0.13	0.29	-0.51	0.13	-0.10	-0.16	-0.09
	(0.91)	(0.74)	(0.71)	(0.91)	(0.74)	(0.71)	(0.59)	(0.32)	(0.51)
Clubs that had banned sponsors and now have no sponsors	**2.31**	**2.24**	**2.28**	0.40	**0.47**	**0.41**	N/A	N/A	N/A
	(0.55)	(0.05)	(0.39)	(0.55)	(0.30)	(0.43)			
Clubs that did not have banned sponsors and now have other sponsors	**0.39**	0.18	**0.41**	**0.39**	0.18	**0.41**	**0.45**	**0.36**	**0.47**
	(0.82)	(0.52)	(0.85)	(0.82)	(0.52)	(0.85)	(0.66)	(0.28)	(0.65)
Clubs that did not have banned sponsors and now have no sponsors	**2.14**	**2.25**	**2.17**	**0.31**	0.39	**0.39**	N/A	N/A	N/A
	(0.16)	(0.31)	(0.20)	(0.37)	(0.46)	(0.47)			

Standard deviation in parentheses. Unit of observation is the club-year. Data includes only 1990, 1995, 2000, 2005, and 2010. Simulations based on estimates in Table 4 column (8). Numbers in bold mean that the difference between the optimal and counterfactual groups is significant at the 95% confidence level

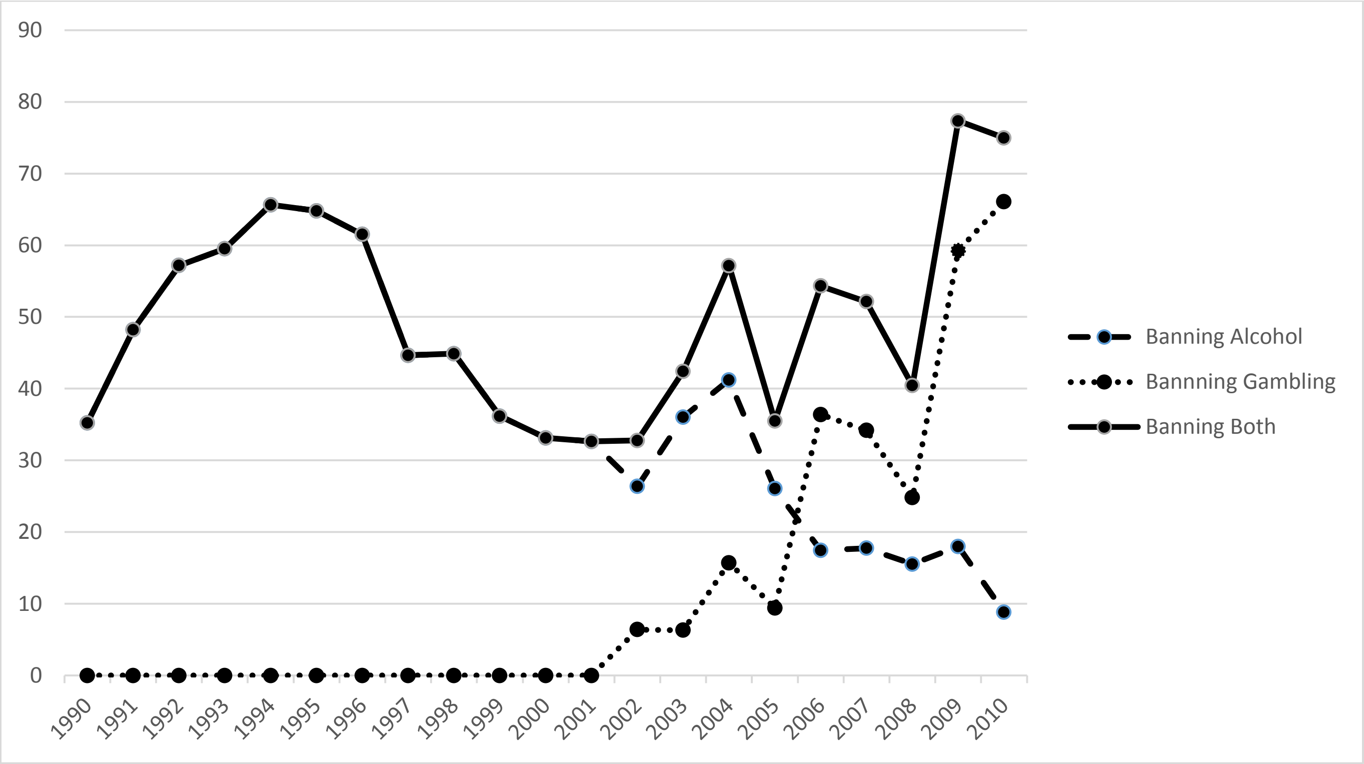
Table 13: Impact of a ban on individual clubs in model without switching costs

	Main specification: Counterfactual matches based on all sponsors in the current year			Counterfactual matches based on a team-specific benchmark drawn from all years of data			Counterfactual matches based on all sponsors in the current year and the following two years of data (2009 and 2011 for the 2010 data)		
	Alcohol	**Gambling**	**Both**	**Alcohol**	**Gambling**	**Both**	**Alcohol**	**Gambling**	**Both**
Constant	1.856***	-0.069	1.746**	0.242	-0.046	0.241	-0.061	-0.199**	-0.188
	(0.664)	(0.436)	(0.751)	(0.361)	(0.175)	(0.379)	(0.329)	(0.084)	(0.339)
Club Performance									
Current year	0.220	-0.161	0.193	0.053*	0.023	0.133	0.061	0.011	0.021
	(0.407)	(0.267)	(0.460)	(0.221)	(0.107)	(0.232)	(0.202)	(0.052)	(0.208)
Accumulated percentage	0.476	-0.517***	0.063	0.310	-0.124	0.139	-0.080	0.061*	-0.048
	(0.290)	(0.190)	(0.328)	(0.158)	(0.077)	(0.166)	(0.144)	(0.037)	(0.148)
Log club revenue	-0.005	0.108*	0.131	0.023	0.028	0.062	-0.028	0.023**	-0.014
	(0.084)	(0.055)	(0.095)	(0.046)	(0.022)	(0.048)	(0.042)	(0.011)	(0.043)
Log club attendance	-0.327	0.027	-0.392	-0.105	-0.016	-0.135	0.117	-0.060**	0.094
	(0.215)	(0.141)	(0.243)	(0.117)	(0.057)	(0.122)	(0.106)	(0.027)	(0.110)
Local weekly earning index	-1.039*	-0.618	-1.763***	-0.270	-0.122	-0.522	0.109	0.158**	0.212
	(0.588)	(0.386)	(0.665)	(0.320)	(0.155)	(0.335)	(0.291)	(0.075)	(0.300)
Population Density	0.001	0.001	0.002	0.000	0.000	0.001	-0.002	-0.001**	-0.002
	(0.003)	(0.002)	(0.004)	(0.002)	(0.001)	(0.002)	(0.002)	(0.000)	(0.002)
R-squared	0.067	0.079	0.084	0.034	0.028	0.039	0.018	0.050	0.016

**significant at the 1% level; ** significant at the 5% level; *significant at the 10% level

Dependent variable is the loss in match value in the counterfactual relative to the simulated optimum. Standard error in parentheses. N=208. Unit of observation is the club-year. Data includes only 1990, 1995, 2000, 2005, and 2010. Simulations based on estimates in Table 4 column (8).

Figure 1: Total Matching Value Loss Year-by-year



Appendix Tables

Table A1: Table 4 with confidence intervals (to be continued)

	Data from 1990-2010 (inclusive)				
Interaction Variables	(1)	(2)	(3)	(4)	(5)
Distance-related interactions					
Distance	-1	-1	-1	-1	-1
Distance×club performance ranking	0.011	**0.096**	**0.196**	-0.371	**0.076**
	[-0.020, 0.187]	[0.002, 0.308]	[0.007, 0.286]	[-0.397, 0.761]	[0.001, 0.238]
Distance×log club attendance	0.139		**0.258**	0.237	
	[-0.319, 0.387]		[0.003, 0.528]	[-3.965, 0.179]	
Distance×log club revenue				0.586	
				[-0.191, 1.997]	
Distance× log sponsor revenue	0.068		0.033	0.094	**0.289**
	[-0.206, 0.483]		[-0.212, 0.400]	[-4.563, 0.256]	[0.080, 0.616]
Distance× int'l sponsor	**0.445**	**0.465**	**0.118**	**0.217**	**0.081**
	[0.096, 0.601]	[0.365, 0.634]	[0.039, 0.365]	[0.095, 1.893]	[0.004, 0.496]
Distance×industry dummies of a sponsor					
Distance ×alcohol manufacturer	-0.582	-0.183	-0.027	-0.037	-0.097
	[-0.860, 0.062]	[-0.293, 0.025]	[-0.163, 0.015]	[-0.987, 0.639]	[-0.747, 0.053]
Distance ×car manufacturer	-12.819	-2.126	-0.087	-6.04	-2.714
	[-18.082, 0.178]	[-8.057, 0.117]	[-4.933, 0.203]	[-12.383, 0.797]	[-6.768, 0.169]
Distance ×airline sponsor	**-0.53**	**-0.201**	**-0.059**	**-0.245**	-0.369
	[-1.093, -0.130]	[-1.212, -0.184]	[-0.353, -0.033]	[-3.957, -0.218]	[-0.640, 0.004]
Distance ×telecommunication sponsor	**0.748**	**0.7**	**0.454**	**0.359**	**0.422**
	[0.335, 0.888]	[0.480, 0.935]	[0.212, 0.621]	[0.444, 3.122]	[0.309, 0.818]
Distance ×gambling sponsor	**0.701**	**0.533**	**0.359**	0.351	**0.627**
	[0.351, 1.002]	[0.407, 0.983]	[0.185, 0.757]	[-0.019, 1.941]	[0.212, 0.723]
Club's performance × log sponsor revenue					
Club performance ranking ×log sponsor revenue	-0.468	**0.277**	-0.343	**-0.434**	**0.643**
	[-0.802, 0.138]	[0.010, 0.543]	[-0.343, 0.145]	[-2.337, -0.137]	[0.231, 0.702]
Promoted to the top league ×log sponsor revenue	**0.1**	**0.059**		**0.192**	
	[0.035, 0.221]	[0.024, 0.256]		[0.105, 1.231]	
Relegated from the top league ×log sponsor revenue	-0.031	-0.072		-0.051	
	[-0.243, 0.081]	[-0.242, 0.161]		[-1.526, 0.057]	
Accumulated % at the top league ×log sponsor revenue	0.164	**0.251**		0.014	
	[-0.082, 0.421]	[0.030, 0.419]		[-0.030, 0.975]	
Log club attendance × log sponsor revenue	**1.185**		**1.095**	**0.632**	
	[0.294, 1.829]		[0.487, 1.182]	[0.529, 6.602]	
Log club revenue × log sponsor revenue				0.502	
				[-0.534, 2.046]	
Club performance ranking ×log sponsor revenue ×int'l sponsor	**0.406**	**0.301**		**0.362**	
	[0.104, 0.700]	[0.250, 0.892]		[0.217, 2.474]	
Previous sponsorship effect	**2.479**	**2.799**	**4.729**	**2.903**	**1.753**
	[0.639, 7.676]	[0.665, 5.862]	[0.605, 9.457]	[1.428, 9.457]	[0.578, 6.791]
Local industry concentration effect	**0.521**	**0.583**	**0.411**	**0.486**	**0.554**
	[0.282, 0.977]	[0.234, 0.650]	[0.269, 0.532]	[0.457, 4.259]	[0.293, 0.776]
Club city's population density ×log sponsor revenue	-0.17	-0.351	**-0.179**	**-0.48**	-0.458
	[-0.750, 0.038]	[-0.690, 0.051]	[-0.401, -0.047]	[-2.458, -0.121]	[-0.456, 0.089]
Club city's weekly earning index ×log sponsor revenue	**0.293**	**0.655**	**0.226**	**0.524**	**0.768**
	[0.074, 0.989]	[0.177, 1.042]	[0.069, 0.544]	[0.082, 2.000]	[0.088, 0.788]
Maximum Score	95.30%	94.93%	95.08%	95.15%	94.42%
# of inequalities	2744	2744	2744	2744	2744

Numbers in bold are significant at the 95% confidence level

Table A1: Table 4 with confidence intervals (continued)

	1979-2010 data	Non-missing data	Only years divisible by 5	
Interaction Variables	(6)	(7)	(8)	(9)
Distance-related interactions				
Distance	-1	-1	-1	-1
Distance×club performance ranking	0.003	-0.443	0.099	**0.235**
	[-0.239, 0.151]	[-2.424, 0.145]	[-0.158, 0.474]	[0.106, 0.453]
Distance×log club attendance	0.012	0.430	0.236	
	[-0.502, 0.467]	[-1.399, 0.695]	[-0.282, 0.570]	
Distance×log club revenue				
Distance× log sponsor revenue	0.197	-0.198	**-2.616**	0.438
	[-0.768, 0.497]	[-3.703, 0.399]	[-3.962, -1.942]	[-0.576, 0.447]
Distance× int'l sponsor	**0.161**	**0.649**	**1.139**	**0.085**
	[0.078, 0.717]	[0.387, 3.519]	[0.786, 1.529]	[0.030, 0.723]
Distance×industry dummies of a sponsor				
Distance ×alcohol manufacturer	**-0.664**	**-2.168**	**1.263**	**0.200**
	[-1.164, -0.046]	[-2.414, -0.032]	[0.980, 2.099]	[0.150, 0.617]
Distance ×car manufacturer	**-0.27**	0.219	0.925	-1.067
	[-2.038, 0.013]	[-2.287, 7.803]	[-2.529, 3.581]	[-3.165, 4.789]
Distance ×airline sponsor	**-0.582**	-0.211	**1.521**	0.248
	[-1.158, -0.139]	[-2.685, 1.166]	[1.344, 2.436]	[-1.044, 0.836]
Distance ×telecommunication sponsor	**0.377**	**0.999**	**2.850**	**0.497**
	[0.366, 0.915]	[0.034, 3.925]	[2.157, 4.440]	[0.183, 2.724]
Distance ×gambling sponsor	**0.423**	**0.986**	-0.478	**0.422**
	[0.052, 1.160]	[0.615, 4.052]	[-0.814, 0.577]	[0.039, 0.621]
Club's performance × log sponsor revenue				
Club performance ranking ×log sponsor revenue	-0.332	**0.359**	-0.479	**0.329**
	[-0.820, 0.118]	[0.020, 3.655]	[-1.199, 0.089]	[0.052, 0.637]
Promoted to the top league ×log sponsor revenue	**0.1**	**0.035**	**-0.296**	
	[0.041, 0.497]	[0.027, 0.878]	[-0.511, -0.151]	
Relegated from the top league ×log sponsor revenue	-0.057	-0.408	**-0.418**	
	[-0.209, 0.155]	[-2.678, 0.011]	[-1.329, -0.173]	
Accumulated % at the top league ×log sponsor revenue	**0.144**	-0.515	0.225	
	[0.027, 0.337]	[-2.710, 0.448]	[-0.070, 0.668]	
Log club attendance × log sponsor revenue	**0.94**	**1.395**	**2.638**	
	[0.297, 1.860]	[0.067, 6.143]	[1.875, 3.598]	
Log club revenue × log sponsor revenue				
Club performance ranking ×log sponsor revenue ×int'l sponsor	**0.203**	**0.411**	**0.504**	
	[0.172, 0.601]	[0.088, 3.373]	[0.144, 0.749]	
Previous sponsorship effect	**1.776**	**2.137**		
	[0.982, 7.541]	[0.662, 6.717]		
Local industry concentration effect	**0.385**	**0.729**	**0.253**	-0.036
	[0.297, 0.849]	[0.320, 2.869]	[0.011, 0.584]	[-0.370, 0.200]
Club city's population density ×log sponsor revenue	-0.427	0.036	-0.005	0.13
	[-0.666, 0.037]	[-1.960, 0.704]	[-0.727, 0.507]	[-0.021, 0.317]
Club city's weekly earning index ×log sponsor revenue	**0.45**	**0.388**	-0.563	0.124
	[0.172, 0.975]	[0.031, 4.682]	[-1.250, 0.055]	[-0.008, 0.753]
Maximum Score	93.98%	94.92%	91.76%	89.80%
# of inequalities	3740	945	716	716

Numbers in bold are significant at the 95% confidence level

Table A2: Different Models for The Impact of a Ban in the Whole Market (as in Table 6)

	Banning Alcohol		Banning Gambling		Banning Both	
	Matching Value Loss	# of Clubs Impacted	Matching Value Loss	# of Clubs Impacted	Matching Value Loss	# of Clubs Impacted
Model 1 (Identical to Table 6)						
Clubs without a match	32.59	4.48	10.82	1.57	43.94	6.05
Clubs with a worse match	5.23	3.43	1.65	1.00	6.33	3.81
Clubs with a better match	-0.17	0.52	-0.16	0.14	-0.24	0.48
Total	37.66	8.43	12.31	2.71	50.03	10.33
Model 3						
Clubs without a match	12.86	4.48	3.06	1.57	17.16	6.05
Clubs with a worse match	9.44	2.95	2.48	0.86	10.44	3.14
Clubs with a better match	-0.13	0.76	-0.29	0.38	-0.12	0.86
Total	22.17	8.19	5.26	2.81	27.49	10.05
Model 6						
Clubs without a match	10.57	4.48	2.95	1.57	14.41	6.05
Clubs with a worse match	3.32	3.05	1.01	0.90	3.23	3.00
Clubs with a better match	-0.28	0.95	-0.24	0.48	-0.26	0.90
Total	13.61	8.48	3.72	2.95	17.38	9.95

Numbers are per year averages (i.e. the values are for each market separately).
N=881. Unit of observation is the club-year. Data includes 1990-2010 inclusive

Table A3: Different Models for Summary Ban in the Whole Market (as in Table 9)

Independent Variable	The Impact of Banning					
	Alcohol	Gambling	Both	Alcohol	Gambling	Both
Model 1 (Identical to Table 9)						
Constant	4.473***	-0.888*	3.079***	4.463***	-0.179	3.748***
	(0.837)	(0.487)	(0.947)	(1.037)	(0.603)	(1.174)
Club Performance						
Current year	1.728***	-0.631*	0.877	1.728***	-0.648*	0.862
	(0.630)	(0.367)	(0.713)	(0.630)	(0.366)	(0.713)
Accumulated	1.397***	-0.725***	1.087**	1.399***	-0.850***	0.969*
percentage	(0.431)	(0.251)	(0.488)	(0.445)	(0.258)	(0.503)
Log club revenue	-0.104	0.405***	0.291*	-0.104	0.394***	0.281*
	(0.137)	(0.080)	(0.155)	(0.137)	(0.080)	(0.155)
Log club attendance	-0.795**	-0.149	-0.940***	-0.795**	-0.126	-0.919**
	(0.323)	(0.188)	(0.366)	(0.324)	(0.188)	(0.367)
Local weekly	-2.256***	-1.457***	-3.157***	-2.244**	-2.316***	-3.967***
earning index	(0.505)	(0.294)	(0.572)	(0.897)	(0.521)	(1.015)
Population Density				0.000	0.006**	0.006
				(0.005)	(0.003)	(0.006)
R-squared	0.044	0.067	0.042	0.044	0.071	0.043
Model 3	1.972***	-0.705**	1.086*	1.705***	-0.435	1.235*
Constant	(0.536)	(0.276)	(0.586)	(0.665)	(0.342)	(0.726)
Club Performance						
Current year	0.987**	-0.405*	0.568	0.994**	-0.411**5	0.565
	(0.404)	(0.208)	(0.441)	(0.404)	(0.208)	(0.441)
Accumulated	1.630***	-0.091	1.558	1.678***	-0.138	1.531***
percentage	(0.276)	(0.142)	(0.302)	(0.285)	(0.147)	(0.311)
Log club revenue	-0.144*	0.190***	0.061	-0.141	0.186***	0.059
	(0.088)	(0.045)	(0.096)	(0.088)	(0.045)	(0.096)
Log club attendance	-0.200	-0.072	-0.261	-0.208	-0.063	-0.256
	(0.207)	(0.107)	(0.226)	(0.208)	(0.107)	(0.227)
Local weekly	-1.035***	-0.450***	-1.474***	-0.711	-0.777***	-1.655***
earning index	(0.324)	(0.167)	(0.354)	(0.575)	(0.296)	(0.628)
Population Density				-0.002	0.002	0.001
				(0.003)	(0.002)	(0.004)
R-squared	0.080	0.036	0.078	0.080	0.038	0.078
Model 6						
Constant	1.405***	-0.402**	0.988***	1.478***	-0.177	1.192***
	(0.308)	(0.161)	(0.342)	(0.382)	(0.198)	(0.423)
Club Performance						
Current year	0.583**	-0.240**	0.329	0.582**	-0.245**	0.325
	(0.232)	(0.121)	(0.257)	(0.232)	(0.121)	(0.257)
Accumulated	0.781***	-0.167**	0.812***	0.768***	-0.207**	0.776***
percentage	(0.159)	(0.083)	(0.176)	(0.164)	(0.085)	(0.182)
Log club revenue	-0.070	0.138***	0.059	-0.0712	0.135***	0.056
	(0.050)	(0.026)	(0.056)	(0.050)	(0.026)	(0.056)
Log club attendance	-0.160	-0.033	-0.225*	-0.157	-0.026	-0.219*
	(0.119)	(0.062)	(0.132)	(0.119)	(0.062)	(0.132)
Local weekly	-0.774***	-0.482***	-1.148***	-0.863***	-0.754***	-1.395***
earning index	(0.186)	(0.097)	(0.206)	(0.330)	(0.172)	(0.366)
Population Density				0.001	0.002*	0.002
				(0.002)	(0.001)	(0.002)
R-squared	0.064	0.071	0.074	0.064	0.075	0.074

***significant at the 1% level; ** significant at the 5% level; * ** significant at the 10% level. Standard errors in parentheses. Dependent variable is the loss in match value in the counterfactual relative to the simulated optimum. N=881. Unit of observation is the club-year. Data includes 1990-2010 inclusive.