OPEN ACCESS
International Journal of Empirical Economics
Vol. 1, No. 3 (2022) 2250010 (24 pages)

DOI: 10.1142/S281094302250010X

Spatial Attendance Spillover in Football Leagues

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Received 6 July 2022
Revised 31 August 2022
Accepted 1 September 2022
Published 30 September 2022

We analyse the spatial attendance spillover applying spatial panel-data models with the Italian Football League data from 2001/2002 to 2016/2017. Our Quasi-Maximum Likelihood empirical results suggest that no significant spatial interaction was evident in earlier seasons (2001–2013), but modest spatial spillover was in play from 2013 to 2016. In addition, cross-quality spillover exists only locally in the same cities. We use numerical simulations to examine the potential impact of such spillover on attendance distribution and then competitive balance; spillover implies an interaction between the two exclusive markets that are the principal sources of competitive imbalance. Our numerical simulations suggest that spatial spillover may create attendance variations across member teams. The final outcome depends on the spillover sign, the network structure, and the market size distribution. Combining the empirical results with numerical simulations, we find that a recent, slightly positive spillover may modestly reduce attendance disparity.

Keywords: Spatial spillover; attendance; attendance disparity; Italian football league.

JEL Classification: L83, L80, Z20

Introduction

Empirical studies on fans' demand for sporting matches have tested the uncertainty of outcome hypothesis, and evaluated inelastic pricing, fan loyalty, and stadium effects (see the review by Krautmann and Hadley (2006), Johnson and Fort (2022), Schreyer and Ansari (2022)). Recently, the research topics have diversified somewhat. Several studies have analysed the competition for fan demand among teams within and across leagues (see for example Winfree *et al.* (2004), Winfree and Fort (2008), Mills *et al.* (2015), Mills *et al.* (2016) and Mondello *et al.* (2017)). Mills *et al.* (2016) considered the importance of among-firm competition based on the product quality. They explored the television viewership of North American major league baseball (MLB), particularly teams in shared markets focusing on cross-quality elasticity. The empirical evidence suggests that teams within shared markets are complementary in terms of high quality, but substitutable in terms of large disparities in quality. Winfree *et al.* (2004) linked space to MLB attendance, and found that the neighbour teams influence the fans' demand for a local team. For example, incumbent team attendance fell when a new (expanded) team moved into the area of the existing team. Such empirical results imply that fans' demand may be affected by the neighbours' effects. Since information and communication technologies, and transportation, have developed rapidly, fans may consider not only the home team characteristics but also those of neighbouring or visiting teams when formulating their demands for home matches.

Here, we use spatial panel data models to study the neighbour and spatial dependence of attendance. Markets that are mutually proximate may share historical and economic ties. Consumer preference tends to be spatially correlated (e.g. Müller and Haase, 2015). Spatial panel data models have been developed to address endogenous spatial spillover or network effects (see Yu *et al.*, 2008). The fact that spatial econometric models capture co-dependency across a known network has been invaluable to economists and regional scientists (Baltagi, 2005). Henrickson (2012) applied spatial models on four major team sports of the North American Leagues (NALs), and found that the spatial spillover in terms of ticket price (a positive relationship between local ticket prices and those of neighbouring games) was significant for all four NALs. However, no prior empirical study had used spatial models to evaluate the attendance data.

In this paper, we apply the spatial panel-data models to analyse the spatial attendance spillover of a professional sports league. As Italian Football League, Serie A, has relatively low sold-out matches than other European football leagues, we analysed Serie A from 2001/2002 to 2016/2017. We found that no significant spatial interaction was evident in earlier seasons (2001–2013), but modest spatial spillover was in play from 2013 to 2016. These findings are robust across the three different weight matrices employed, the inverse distance-based, the dynasty-based, and the shared market-based spatial weight matrices.

Next, we aim to examine the potentially important issue of whether spatial attendance spillover enhances or worsens attendance disparity and eventually the competitive imbalance (CIB). Professional sports teams generally enjoy local monopolies or oligopolies given their exclusive territories; the resulting revenue disparities are the principal sources of CIB. Spatial attendance spillover implies an interaction between two exclusive markets, suggesting that the mere existence of, or changes in, such spillover may affect attendance disparity. We find that the final outcome depends on the direction of spillover, the network structure, and the territory market size. Combining these numerical simulations with the empirical results, we may deduce that a recent, slightly positive spillover, estimated at about 0.1, may modestly reduce variations in attendance across member teams by about 10% of standard deviation. This is the first study to conduct numerical simulations and investigate the effect of spatial spillover on attendance disparity.

The paper is structured as follows: The second section presents the econometric models used. The third section describes the sample data and specifies the attendance regression employed. The fourth section presents the principal empirical results. The fifth section presents the numerical simulations. Finally, the sixth section offers conclusions and mentions our planned future work.

Spatial Panel-Data Models

Consider the following spatial autoregressive (SAR) panel-data model:

$$y_{ijt} = \rho y^*_{ijt} + x'_{ijt}\beta + u_{ijt}, \quad u_{ijt} = \alpha_i + \gamma_j + \lambda_t + \varepsilon_{ijt}, \tag{1}$$

for $i, j = 1, \ldots, N$, $j \neq i$ and $t = 1, \ldots, T$, where y_{ijt} is the scalar-dependent variable given by the logged daily game attendance of a home team i against a visiting team j in season t. The $x_{ijt} = (x^1_{ijt}, \ldots, x^K_{ijt})'$ is a $K \times 1$ vector of exogenous regressors with a $K \times 1$ vector of parameters, $\beta = (\beta 1, \ldots, \beta_K)'$. The SAR model captures spatial correlation within a system via the dependence imposed on the spatially-dependent variable y^*_{ijt} defined as

$$y^*_{ijt} \equiv \sum_{j=1}^{N} w_{ij} y_{ijt} = w_i y_{it} \quad \text{with} \quad \underset{N\times 1}{y_{it}} = (y_{i1t}, \ldots, y_{iNt})',$$

where $w_i(w_{i1}, \ldots, w_{iN})$ denotes a $1 \times N$ vector of (non-stochastic) predetermined spatial weights with $w_{ii} = 0$ to prevent self-influence. The $N \times N$ spatial weight matrix, W, is row-standardized (the row sum is one). As y^*_{ijt} is correlated with ε_{ijt}, the parameter $\rho$is endogenous. We control for the home team-specific effect α_i, the visiting team-specific effect γ_j, and season effects λ_t; all are unobserved but possibly correlated with y^*_{ijt} and x_{ijt}.

The spatial Durbin model (SDM) allows the explanatory variables of one unit to impact the dependent variable of another unit both directly and indirectly via their spatial impacts on the dependent variable. For example, an improvement in school quality in one area directly improves house prices in neighbouring areas whose residents may access the newly improved schools. Also, an indirect effect is in play; rising house prices in one area increase prices in neighbouring areas. Hence, we also consider the SDM:

$$y_{ijt} = \rho y^*_{ijt} + x'_{ijt}\beta + x^{*}_{ijt}{}'\delta + u_{ijt}, \quad u_{ijt} = \alpha_i + \gamma_j + \lambda_t + \varepsilon_{ijt}, \qquad (2)$$

where

$$\underset{K\times 1}{x^*_{ijt}} = (x^{1*}_{ijt}, \ldots, x^{K*}_{ijt})' \equiv \left(\sum_{j=1}^{N} w_{ij} x^1_{ijt}, \ldots, \sum_{j=1}^{N} w_{ij} x^K_{ijt}\right)'.$$

By applying the appropriate three-way within-transformation to Eqs. (1) and (2), we can remove all of α_i, γ_j, and λ_t. Next, to deal with the endogeneity of the spatial lagged variable y^*_{ijt}, we use the quasi-maximum likelihood (QML) technique to obtain consistent estimators of ρ and β.

The Data and the Attendance Regression Specifications

We collect attendance and performance data for Serie A league from the 'transfermarkt' website (www.transfermarkt.co.uk) and betting odds from the Football-Data website (http://www.football-data.co.uk).Although the latter website contains a great deal of European football league (EFL) betting data, we use the fixed decimal betting odds provided by William Hill only because they include historical data for Serie A. As our data access was limited, we collect information from 2001/2002 to 2016/2017 (16 seasons). We retrieve information on 5,544 matches among 42 teams in Serie A first division. The summary of the sample is revealed in Table 1. As Serie A is characterized by relatively few sold-out matches (unlike other major European football leagues), censoring is not a serious problem in this data set. Because of relegation and promotion, several (i, j) pairs may be observed only once or a few times. We then construct balanced panel data; there was a possibility that we would lose a great deal of information because only a few teams may have remained in the first division for all 16 seasons. To mitigate this concern, we construct five sets of balanced panel data for 2001/02–2003/04, 2004/05–2006/07, 2007/08–2009/10, 2010/11–2012/13, and 2013/14–2016/17 (each sample covers

Table 1. Descriptive statistics.

Variable	Mean	Std. Dev.	Min	Max
Attendance	23,663	15,203	100.0	81,955
GU	0.141	0.097	0.000	0.500
CLQU	1.912	4.597	0.000	61.000
RU	1.527	4.321	0.000	85.000
HGOAL	1.283	0.456	0.000	4.000
HWIN	0.497	0.174	0.000	1.000
HOLIDAY	0.872	0.334	0.000	1.000
NIGHT	0.289	0.453	0.000	1.000

Note: The total number of observations was 5,544.

three or four seasons).[1] There have been a few literatures analysing stadium attendance demand for Serie A (Bond and Addesa, 2020; Jang and Lee, 2021) and to the best of our knowledge, this is the first study that explore attendance spillover effects in Serie A.

The dependent variable is the logged attendance at individual matches. We include outcome uncertainties and other control variables as regressors. We consider three different types of match uncertainty, denoted game uncertainty (GU), Champions League qualification uncertainty (CLU), and relegation uncertainty (RU). GU is the absolute difference in win probability between the home and visiting teams. This is identical to the absolute distance of the probability of a home team win from 0.5 given by

$$GU_{ijt} = |p_{ijt} - 0.5|, \tag{3}$$

where p_{ijt} is the probability that a home team i wins against a visiting team j in season t (see Berkowitz *et al.* (2011)) for various measures of GU). We use betting odds to obtain an estimate of p_{ijt}. We convert the odds to implied probabilities.[2] As a robustness check, we also include p_{ijt} and its square instead of GU. In all seasons, Serie A teams compete not only for a league championship but also to qualify for an international Champions League (CL). Thus, the fan demand for individual matches may be influenced by the CL. In this context, any uncertainty in terms of eventual CL qualification (CLU) may be an important demand determinant, especially if a team ranks fourth near at the end of a season (and is thus almost out of contention for the CL). Fans pay more attention to team performance if the team is in a tight race for CL qualification. We measure CLU as the absolute difference in points (point_{it})

[1] Clubs not survived consecutive three or four years were dropped for balanced data.

[2] We calculated implied probability as $p_i = (1/d_i)/(1/d_1 + 1/d_2 + 1/d_3)$, here, (d_1, d_2, d_3) and (p_1, p_2, p_3) are the odds and probabilities of a home win, a home loss, and a draw, respectively.

gained by a home team in a match and the points (point_{Ct}) gained by the lowest-ranked CL-qualified teams on each game day: $|\text{point}_{it} - \text{point}_{Ct}|$. As the top three Serie A teams proceeded to the CL in 2012/2013, point_{Ct} represents the points of the third-ranked team prior to a game. Thus, CLU_{ijt} is absolute difference between team i and third-ranked team in 2012/2013 season. CLU_{ijt} represents the status of team i in terms of CL qualification prior to the game between home team i and visiting team j in season t. As discussed by Jang and Lee (2021), CLU_{ijt} may be local in the sense that it is relevant only to the top teams that may possibly advance to the CL. We construct a dummy variable: CL contention (CLDUM), which is 1 if a team is ranked higher than eighth (seventh from the 2011/2012 season), and otherwise 0. Thus, we construct $\text{CLQU}_{ijt} = |\text{point}_{it} - \text{point}_{Ct}| \cdot \text{CLDUM}_{it}$.

Relegation/promotion is another distinctive characteristic of open leagues such as Serie A. Although fans of weaker teams may not expect those teams to win the league championship or qualify for the CL, they are concerned that their team remain in the first division; this is an important demand determinant. We measure relegation uncertainty (RU) similarly to CLQU. We calculate the absolute difference between the points of a home team and the points (point_{Rt}) of the highest-ranked team of the relegated contenders: $|\text{point}_{it} - \text{point}_{Rt}|$. As the bottom three teams in Serie A are relegated to Serie B, point_{Rt} represents the points of the 18th-ranked team before the match. RU is also local, being relevant to the fan demand of the bottom teams. RDUM[3] is 1 if a team is ranked lower than 17th and 0 otherwise. RU_{ijt} represents the status of team i (in terms of RU) before the game between the home team i and the visiting team j in season t ($\text{RU}_{ijt} = |\text{point}_{it} - \text{point}_{Rt}| \cdot \text{RDUM}_{it}$). We also include other control variables used in previous studies, such as the winning record and the goals per game. The team-specific winning percentage (HWIN) captures home team quality whereas goals per game for home teams (HGOAL) measure offensive quality. We also control holiday and night matches. To control for team-specific effects such as stadium capacity and the local population, we allow the existence of unobserved individual team and time effects. Specific descriptions for variables used in spatial regression are presented in Table 1.

Empirical Results

We first test for cross-sectional dependence (CSD) using the residuals from fixed-effects regression; we apply the CD statistic of Pesaran (2004, 2015). The test results (Table 2) reveal that the null hypothesis of no or weak CSD is strongly rejected except for the 2007–2009 seasons, suggesting that CSD is pervasive in terms of

[3] Although the dummies CLDUM and RDUM are *ad-hoc*, Jang and Lee (2021) found that estimations derived using these dummies were qualitatively robust even when the dummies differed somewhat.

Table 2. Pesaran's test for cross-sectional dependence.

Period	Teams	Test Statistics	p-value
2001–2003	11	2.202	0.028
2004–2006	15	2.240	0.025
2007–2009	15	−0.640	0.522
2010–2012	15	3.249	0.001
2013–2016	14	1.937	0.053

individual Serie A team attendance. We use three different spatial weight matrices to capture potentially complex spatial interactions. The first is the distance between the two teams. This popular measure[4] assumes that the strengths of neighbouring effects depend on the inverse distance. We use row-sum normalization (sum of one). Therefore, the weight decreases as the distance between the two clubs is far. Figure 1 shows the locations of Serie A teams. For example, the distance-based weighting implies that Inter-Milan (located in the North) lacks any strong ties with Bari (located in the South). If a spatial lag parameter is positive, attendance between the two clubs is positively correlated and the correlation increases as the distance between the two clubs is closer.

Next, we select a "dynasty" of the top four teams: Juventus, Milan, Inter, and Roma. Table 3 lists the number of seasons for which these teams were in the top two from 1930 to 1999. This selection may be *ad-hoc*, but we find that the estimations are qualitatively similar when we choose different dynasties. Dynasty weight matrix express connectivity between two teams. The element of dynasty weight matrix is set as $w_{ij} = 1$ if j club belongs to dynasty clubs. This weight matrix assumed that matches between two clubs are connected to matches of dynasty clubs in a certain round. If ρ shows a negative sign, it indicates that attendance of a club is affected by the attendance of a dynasty club negatively.

The third sets of weights, shared market weight matrix, also indicates spatial connectivity of the clubs. We assigned neighbour effects to only multiple teams located within the same cities. Table 4 shows that five cities (Genoa, Milan, Rome, Turin, and Verona) host two teams each. The element of shared market weight matrix is defined as $w_{ij} = 1$ if $i \neq j$, and i and j clubs are located in the same city. This weight matrix considered that only clubs within the same city affect each other. Positive spatial autoregression coefficient presents that attendance of two clubs in the same city is positively related.

[4]Blonigen *et al.* (2007) used distance between two countries as a weight matrix to find out spatial interdependence of FDI activity. You and Lv (2018) also used distance between two countries as a weight matrix and they analysed the neighbouring effects in CO_2 emission.

Fig. 1. Locations of individual teams in Italian Football League (Seria A).

Table 3. The number of seasons ranked at Top 2 over the period 1930–1999.

Teams	Freq.	Teams	Freq.
Juventus	51	Torino	9
Milan	27	Bologna	8
Inter	23	Fiorentina	7
Roma	17	Ambrosiana-Inter	6
Napoli	11	Lazio	4

Table 4. Teams sharing a city.

City	Teams	Teams
Verona	Chievo Verona	Hellas Verona
Milan	Inter Milan	AC Milan
Rome	Roma	Lazio
Turin	Jeventus	Torino
Genoa	Genoa	Sampdoria

In Tables 5–7, we present the estimations of the non-spatial fixed-effect model (FEM), and the SAR and SDM with three different weights.[5] In all estimations, we control for unobserved home team, visiting team, and time effects, estimated using the QML method. Table 5 presents the estimations derived using the distance-based spatial weight matrix. As a benchmark comparison, we also include the FEM estimations, which are both statistically significant and consistent with *a priori* expectations. The impacts of GU on attendance are significant and positive in the earlier periods, but the magnitude thereof declines from 0.59 in 2001/02–2003/04 to 0.21 in 2007/08–2009/10 and becomes insignificant from 2010 onwards.[6] CLQU is not a significant determinant of attendance in any sub-period; RU became significant only recently (2013/14–2016/17). HWIN boosts attendance significantly in almost all periods except 2001/02–2003/04.

We now turn to the estimations of the SAR and SDM; we use distance-based weights to construct spatial lagged variables and regressors. The SAR coefficients are insignificant and negligible in most sub-periods, except for 2013–2016, when the spillover impacts were modest (0.11 and 0.10, respectively). However, the SDM coefficients are insignificant and negligible in all seasons. Thus, the impacts of GU, CLQU, RU, and HWIN are similar to those estimated by the FEM.

Tables 6 and 7 present the estimations derived using the dynasty-based and shared market-based spatial weight matrices. Both sets of results are qualitatively and quantitatively similar to those of Table 5. In particular, the SAR coefficients became significant and positive only recently (2013–2016), with modest spillover impacts of 0.09–0.11. Overall, spatial attendance spillover was historically insignificant in Serie A, becoming significant only recently. This may reflect strong fan loyalty. However, there is a noticeable finding in Table 7. The Durbin model is significant

[5]To save space, we do not report our estimates of other control variables. However, the signs of their impacts are generally consistent with our *a priori* expectations.

[6]This result is consistent with Johnson and Fort (2022). They reviewed empirical works analyzing uncertainty outcome hypothesis (UOH) and found that most empirical works with soccer leagues have not supported UOH.

Table 5. Attendance estimation of the spatial model with distance weight.

	2001–2003			2004–2006			2007–2009			2010–2012			2013–2016		
Variables	FE	SAR	SDM	FE	SAR	SDM	FE	SAR	SDM	FE	SAR	SDM	FE	SAR	SDM
GU	0.592**	0.596**	0.595**	0.359**	0.357**	0.351**	0.205*	0.208*	0.208*	0.332†	0.333†	0.333†	0.061	0.066	0.069
	(0.160)	(0.154)	(0.154)	(0.129)	(0.126)	(0.126)	(0.093)	(0.091)	(0.091)	(0.182)	(0.179)	(0.179)	(0.106)	(0.104)	(0.104)
CLQU	−0.004	−0.005†	−0.005†	0.002	0.002†	0.002†	0.002	0.002	0.003	0.006	0.006†	0.006†	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
RU	0.005	0.005	0.005	0.002	0.002	0.002	−0.000	−0.000	−0.000	−0.005	−0.005	−0.005	0.008**	0.008**	0.008**
	(0.007)	(0.007)	(0.007)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
HGOAL	−0.003	−0.003	−0.004	0.079*	0.081*	0.073*	0.028	0.028	0.026	0.057	0.058	0.058	0.016	0.016	0.020
	(0.034)	(0.033)	(0.033)	(0.036)	(0.035)	(0.036)	(0.026)	(0.025)	(0.026)	(0.049)	(0.048)	(0.048)	(0.026)	(0.026)	(0.026)
HWIN	−0.055	−0.055	−0.054	0.233*	0.231*	0.233*	0.148*	0.149*	0.149*	0.455**	0.449**	0.448**	0.292**	0.295**	0.296**
	(0.118)	(0.114)	(0.115)	(0.094)	(0.092)	(0.092)	(0.075)	(0.073)	(0.073)	(0.140)	(0.138)	(0.140)	(0.082)	(0.081)	(0.081)
Spatial term															
ATT		0.095	0.095		0.042	0.049		−0.038	−0.037		−0.061	−0.061		0.106†	0.102†
		(0.068)	(0.068)		(0.046)	(0.046)		(0.067)	(0.067)		(0.087)	(0.087)		(0.055)	(0.055)
HGOAL			−0.013			−0.113			−0.036			−0.005			0.039
			(0.093)			(0.076)			(0.078)			(0.136)			(0.060)
Observations		528	528	810	810	810	810	810	810	810	810	810	1,008	1,008	1,008
R^2	0.495			0.434			0.381			0.276			0.313		
Home Effects, Visitor Effects, Season Effects															

Note: $^{**}p < 0.01$, $^{*}p < 0.05$, and $^{\dagger}p < 0.1$.

Table 6. Attendance estimation of the spatial model with dynasty weight.

	2001–2003		2004–2006		2007–2009		2010–2012		2013–2016	
Variables	SAR	SDM	SAR	SDM	SAR	Variables	SAR	SDM	SAR	SDM
GU	0.602**	0.602**	0.355**	0.366**	0.200*	0.196*	0.332†	0.345†	0.060	0.060
	(0.155)	(0.155)	(0.126)	(0.126)	(0.092)	(0.092)	(0.179)	(0.179)	(0.104)	(0.104)
CLQU	−0.005†	−0.005†	0.002	0.002†	0.002	0.002	0.006	0.007†	0.002	0.002
	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)
RU	0.004	0.004	0.002	0.002	−0.001	0.000	−0.005	−0.005	0.008**	0.008**
	(0.007)	(0.007)	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)	(0.006)	(0.003)	(0.003)
HGOAL	−0.003	−0.004	0.079*	0.068†	0.028	0.029	0.058	0.056	0.014	0.014
	(0.033)	(0.033)	(0.035)	(0.036)	(0.025)	(0.025)	(0.048)	(0.048)	(0.026)	(0.026)
HWIN	−0.054	−0.051	0.236*	0.236*	0.148*	0.151*	0.448**	0.436**	0.299**	0.299**
	(0.114)	(0.115)	(0.092)	(0.092)	(0.073)	(0.073)	(0.138)	(0.138)	(0.081)	(0.081)
Spatial term										
ATT	−0.058	−0.058	0.068	0.075	0.031	0.033	−0.036	−0.040	0.089†	0.088†
	(0.060)	(0.060)	(0.059)	(0.059)	(0.057)	(0.057)	(0.070)	(0.070)	(0.052)	(0.053)
HGOAL		−0.020		−0.120†		−0.085*		−0.115		0.005
		(0.050)		(0.063)		(0.039)		(0.086)		(0.042)
Observations	528	528	810	810	810	810	810	810	1,008	1,008
Home Effects, Visitor Effects, Season Effects										

Note: ** $p < 0.01$, * $p < 0.05$, and † $p < 0.1$.

Table 7. Attendance estimation of the spatial model with shared market weight.

	2001–2003		2004–2006		2007–2009		2010–2012		2013–2016	
Variables	SAR	SDM	SAR	SDM	SAR	SDM	SAR	SDM	SAR	SDM
GU	0.605**	0.611**	0.361**	0.357**	0.205*	0.199*	0.332†	0.331†	0.057	0.060
	(0.155)	(0.156)	(0.126)	(0.126)	(0.091)	(0.091)	(0.179)	(0.179)	(0.103)	(0.103)
CLQU	−0.004	−0.004	0.002†	0.002†	0.002	0.002	0.006	0.006	0.002	0.002
	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)
RU	0.005	0.005	0.002	0.002	−0.000	−0.000	−0.005	−0.005	0.008**	0.008**
	(0.007)	(0.007)	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)	(0.006)	(0.003)	(0.003)
HGOAL	−0.002	−0.005	0.077*	0.077*	0.028	0.026	0.058	0.058	0.021	0.028
	(0.033)	(0.034)	(0.035)	(0.035)	(0.025)	(0.025)	(0.048)	(0.048)	(0.026)	(0.026)
HWIN	−0.060	−0.060	0.241**	0.246**	0.152*	0.154*	0.454**	0.455**	0.285**	0.257**
	(0.114)	(0.114)	(0.093)	(0.093)	(0.073)	(0.073)	(0.137)	(0.137)	(0.080)	(0.080)
Spatial term										
ATT	−0.061	−0.061	0.033	0.030	0.040	0.050	0.012	0.011	0.102**	0.109**
	(0.045)	(0.045)	(0.047)	(0.047)	(0.033)	(0.034)	(0.051)	(0.051)	(0.028)	(0.028)
HGOAL		0.012		0.046		−0.058*		0.009		−0.067*
		(0.041)		(0.059)		(0.029)		(0.067)		(0.026)
Observations	528	528	810	810	810	810	810	810	1,008	1,008
Home Effects, Visitor Effects, Season Effects										

Note: ** $p < 0.01$, * $p < 0.05$, and † $p < 0.1$.

only in Table 7 and this implies that the performance of individual teams influences their neighbours' attendance directly. Comparing the weight matrices that are based on shared market in Table 7 but are based on distance in Table 5 and dynasty in Table 6, it may be that the Durbin spillover is more localized and it may occur only statistically significantly between teams in the same city. Our Durbin coefficient is related to cross-quality elasticity in shared markets that was analysed with MLB television viewership by Mills *et al.* (2016). Its estimate is negative and then it implies substitutable in terms of performance quality.

Next, we present the spatial estimations in terms of direct, indirect, and total effects (see LeSage and Pace, 2014). We rewrite Eqs. (1) and (2) as their spatial system representations:

$$y_t = \rho W y_t + X_t\beta + u_t, \tag{4}$$

$$y_t = \rho W y_t + X_t\beta + W X_t\delta + u_t, \tag{5}$$

where $W = \{w_{ij}\}_{i,j=1}^{N}$ is the $N \times N$ spatial weight matrix. Then, Eqs. (4) and (5) can be expressed as follows:

$$\begin{aligned} y_t &= (I_N - \rho W)^{-1}(X_t\beta + u_t) \\ &= \sum_{k=1}^{K}(I_N - \rho W)^{-1}\beta_k x_{kt} + (I_N - \rho W)^{-1}u_t, \end{aligned} \tag{6}$$

$$\begin{aligned} y_t &= (I_N - \rho W)^{-1}(X_t\beta + W X_t\delta + u_t) \\ &= \sum_{k=1}^{K}(I_N - \rho W)^{-1}\beta_k x_{kt} + (I_N - \rho W)^{-1} W\delta_k x_{kt} + (I_N - \rho W)^{-1}u_t. \end{aligned} \tag{7}$$

The impacts of a change in the kth time-varying regressor are given by the $N \times N$ matrices of the partial derivatives:

$$\frac{\partial y_t}{\partial x_{kt}} = (I_N - \rho W)^{-1}\beta_k, \quad k = 1, \ldots, K, \tag{8}$$

$$\frac{\partial y_t}{\partial x_{kt}} = \{(I_N - \rho W)^{-1}\beta_k + (I_N - \rho W)^{-1} W\delta_k\}, \quad k = 1, \ldots, K. \tag{9}$$

Note that the diagonal elements of Eqs. (8) and (9) are direct impacts that differ across the cross-sectional units; the off-diagonal terms (indirect impacts) are not zero, and the matrices are not symmetric. We thus have N direct effects and $N(N-1)$ indirect effects. LeSage and Pace (2014) suggest reporting only three summary measures: The average of the N diagonal elements (a measure of the direct effect); the average of the $N(N-1)$ off-diagonal elements (the average indirect effect); and the average total effect (the sum of the direct and indirect effects). In spatial models, the coefficient of an explanatory variable cannot be interpreted as a marginal effect that is also a function of the spatial parameter. A team in a spatial model is thus simultaneously exporting spillovers to and importing spillovers from its neighbours. The indirect effects measure the magnitude of the spillovers that are simultaneously imported and exported. An indirect effect can be interpreted as the spillover exported by a team, and is the average change in the dependent variable of all other teams, following a change in the independent variable of one particular team. This may be interpreted as the magnitude of spillover imported by a unit, thus the average change in the dependent variable for a particular team follows the changes in the independent variables of all other teams.

Tables 8–10 report the direct, indirect, and total effects of regressors on attendance for the 2013–2016 seasons, but only when the SAR coefficient is significant. From Table 8 (derived using the inverse distance-based spatial weight matrix), we find that both the direct and indirect effects are always positive, but the former is substantially larger than the latter. Thus, the estimated total effects are slightly larger than those reported in Table 5. Further, the impacts of HWIN and RU are statistically significant. An increase in the HWIN of a team directly improves attendance; fans are drawn to high-quality home teams. In addition, the outward spillover effect

Table 8. Marginal effects in 2013–2016: SAR with distance weight.

	Direct		Indirect		Total	
	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat
GU	0.066	0.640	0.008	0.590	0.074	0.640
CLQU	0.002	1.160	0.000	1.000	0.003	1.160
RU	0.008	2.630	0.001	1.480	0.009	2.610
HGOAL	0.016	0.620	0.002	0.590	0.018	0.620
HWIN	0.295	3.660	0.035	1.570	0.330	3.560

Table 9. Marginal effects in 2013–2016: SAR with dynasty weight.

	Direct		Indirect		Total	
	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat
GU	0.060	0.580	0.006	0.550	0.066	0.580
CLQU	0.002	1.140	0.000	0.960	0.002	1.140
RU	0.008	2.660	0.001	1.350	0.009	2.640
HGOAL	0.014	0.540	0.001	0.510	0.015	0.540
HWIN	0.299	3.710	0.029	1.410	0.328	3.590

Table 10. Marginal effects in 2013–2016: SAR and SDM with shared market weight.

	Direct		Indirect		Total	
	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat
			SAR			
GU	0.057	0.550	0.003	0.550	0.061	0.550
CLQU	0.002	1.110	0.000	1.070	0.002	1.110
RU	0.008	2.720	0.000	2.170	0.009	2.720
HGOAL	0.021	0.830	0.001	0.800	0.023	0.830
HWIN	0.287	3.570	0.017	2.560	0.304	3.560
			SDM			
GU	0.060	0.580	0.004	0.570	0.064	0.580
CLQU	0.002	1.050	0.000	1.030	0.002	1.050
RU	0.008	2.630	0.001	2.170	0.009	2.630
HGOAL	0.024	0.920	−0.037	−2.420	−0.013	−0.420
HWIN	0.259	3.200	0.016	2.500	0.275	3.200

on the attendances of other teams is accompanied by an inward spillover effect. Hence, the effect of HWIN (home team quality) on attendance is greater than any neighbour effect. The estimation results of Table 9 (derived using the dynasty-based weight matrices) are qualitatively similar to those reported above. However, those of Table 10 (derived using shared market-based weight matrices) are somewhat different. The negative and significant Durbin estimate of HGOAL in Table 7 results in lesser effect of performance on attendance. The indirect effect of HWIN on attendance is only 0.013 in Table 10 while it is 0.034 in Tables 8 or 9. One unit increase in the win of a team draws more of its attendance and there is a positive outward spillover effect which comes back to increase its attendance because of positive inward spillover effect. This is common in Tables 8–10. However, the significant Durbin estimate leads to another spillover result. One unit increase in goals of a team draws more of its attendance and simultaneously it causes to decrease its neighbour's attendance in a shared market. The decrease comes back to decrease its attendance because of inward spillover effect.

Numerical Analyses of the Effect of Spatial Spillover on Competitive Balance

The spatial spillover effect may influence the distributions of attendance. Under the profit-maximization hypothesis, the principal source of competitive balance (CB) is the disparity of marginal revenue across member teams attributable to territorial market disparity.[7] Given a certain level of such disparity, the emergence of spatial spillover may change the attendance distribution and thus the distribution of marginal revenue. We address the important issue of whether spatial attendance spillover improves or worsens attendance disparity and eventually, CB. The final outcome depends on the sign of the SAR coefficient, the network structure (proxied by the spatial weights), and the distribution of territorial market sizes. To investigate the effect of spatial spillover on attendance disparity, we perform a numerical simulation comparing the non-spatial model and the SAR as follows:

$$\text{The non-spatial model: } y_i = \alpha + u_i. \tag{10}$$

$$\text{The spatial model (SAR): } y_i = \rho y_{ij}^* + \alpha + u_i \rightarrow y = (I_N - \rho W)^{-1}(\alpha + u). \tag{11}$$

For simplicity, we do not include any regressor other than a constant term. We then compare attendance variations with and without spatial dependence using Eqs. (10) and (11). We set $\alpha = 20{,}000$ and generate a u_i that is normally distributed with a zero mean and a standard deviation of 10,000. We set the range of the SAR parameter to $\rho = (-0.5, -0.3, -0.1, 0.1, 0.3, 0.5)$ and the numbers of teams, N to 10 or 20. The number of replications is 100,000.

We consider different network structures. Cross-sectional dependence is usually characterized by a physical measure such as distance or contiguity. The first weight matrix (W1) assumes that all member teams are assigned an equal weight, in which case, we have a network that might be considered complete. This spatial structure is not entirely practical because it assumes that every combination of two paired teams is associated with an identical spillover. For example, the spillover effect of Manchester United on Manchester City (located in the same city) is assumed to be the same as that imposed on Southampton (in the far south), but also all other teams of the English Premiere League. The second weight matrix (W2) insists that each team has only two neighbours in either direction and no ties with any other team. Thus, each team has at least two neighbours and/or a maximum of four neighbours. The third weight matrix (W3) is similar to W2, but assumes that a team has only one neighbour in either direction. Assuming that space is horizontal (the earth, for our purposes, is flat), a team in either the far east or far west has only one border (one neighbour) and all other teams two borders (two neighbours). Therefore, W2 and W3 impose arbitrary cut-offs of neighbour numbers (in the sense that such numbers correlate with attendances). Such cutoffs are likely to be based on borders within shared markets. The fourth weight matrix (W4) is based on distance; we do not impose any cutoff. Again assuming that space is horizontal, the first and last

[7] See Fort and Quirk (1995).

teams are located in the far west and far east, respectively, and the other teams in the middle. The nearest-neighbour distances are assumed to be equal (for simplicity). The elements of W4 depend on the inverse distance between any two teams; thus, the nearest neighbour has the largest weight. In summary, W1 and W4 assume that all teams are neighbours, but the extent of cross-sectional dependence between any pair of teams differs in W4 but is identical in W1.

We write the first weight matrix (W1) in Eq. (12) below. We set all diagonal elements to zero, and assign the same values to all other elements after row-normalization for $N = 10$. Thus, $w_{ij} = 1/(N-1) = 1/9$ for all $i \neq j$

$$\mathrm{W1} = \begin{bmatrix} 0 & 0.111 & 0.111 & \cdots & \cdots & 0.111 \\ 0.111 & 0 & 0.111 & \cdots & \cdots & 0.111 \\ \vdots & & & & & \\ 0.111 & 0.111 & \cdots & \cdots & 0.111 & 0 \end{bmatrix}. \tag{12}$$

The first row of the spatial weight matrix represents the spatial structure of team 1. Next, W2 is given in Eq. (13), in which team 1 has only two neighbours (teams 2 and 3), but team 3 has four neighbours (teams 1, 2, 4, and 5). Similarly, W3 is given in Eq. (14).

$$\mathrm{W2} = \begin{bmatrix} 0 & 0.5 & 0.5 & 0 & & \cdots & \cdots & 0 \\ 0.33 & 0 & 0.33 & 0.33 & 0 & \cdots & \cdots & 0 \\ 0.25 & 0.25 & 0 & 0.25 & 0.25 & 0 & \cdots & 0 \\ \vdots & & & & & & & \\ 0 & 0 & \cdots & \cdots & 0 & 0.5 & 0.5 & 0 \end{bmatrix}, \tag{13}$$

$$\mathrm{W3} = \begin{bmatrix} 0 & 1 & 0 & & \cdots & \cdots & 0 \\ 0.5 & 0 & 0.5 & 0 & \cdots & \cdots & 0 \\ 0 & 0.5 & 0 & 0.5 & 0 & \cdots & 0 \\ \vdots & & & & & & \\ 0 & 0 & \cdots & \cdots & 0 & 1 & 0 \end{bmatrix}. \tag{14}$$

In Eq. (15), we construct W4 in terms of (inverse) distances. The first row measures the spatial weights for team 1, from which we find that $w_{12} = 0.353$ is the largest because team 2 is the nearest neighbour, whereas $w_{110} = 0.039$ is the smallest because team 10 is the furthest neighbour.

$$\mathrm{W4} = \begin{bmatrix} 0 & 0.353 & 0.177 & 0.118 & \cdots & 0.039 \\ 0.270 & 0 & 0.270 & 0.134 & \cdots & 0.034 \\ 0.122 & 0.244 & 0 & 0.244 & \cdots & 0.035 \\ \vdots & & & & & \\ 0.039 & 0.044 & \cdots & \cdots & 0.353 & 0 \end{bmatrix}. \tag{15}$$

Table 11. Comparison of standard deviations of attendance in non-spatial and spatial models.

ρ	−0.5	−0.3	−0.1	0.1	0.3	0.5
			$N = 10$			
w_1	1.059*	1.034	1.011	0.989	0.968	0.947
w_2	1.135	1.061	1.014	0.992	0.998	1.044
w_3	1.308	1.107	1.018	0.996	1.033	1.150
w_4	1.081	1.042	1.014	0.990	0.976	0.970
			$N = 20$			
w_1	1.027	1.016	1.005	0.995	0.984	0.974
w_2	1.109	1.045	1.009	0.998	1.021	1.098
w_3	1.273	1.090	1.013	1.002	1.054	1.197
w_4	1.046	1.023	1.009	0.996	0.992	0.998

Note: *Standard deviation in spatial model in Eq. (6)/standard deviation in non-spatial model in Eq. (5).

In Table 11, we compare the differences between the average standard deviations of attendance obtained from the non-spatial model in Eq. (10) and the spatial model in Eq. (11); we construct the ratios of the two standard deviations. If a ratio is greater than one, the variation in attendance imposed by the spatial model is greater than that imposed by the non-spatial model. In such a case, we would conclude that the spatial spillover creates a competitive imbalance. On the other hand, if a ratio is less than one, the spatial spillover tends to reduce the attendance disparity (AD). In the upper panel of Table 11, we report the outcomes for all four weight matrices with $N = 10$. When the SAR parameter ρ is negative, the ratios are greater than one in all cases. The ratio increases as ρ becomes more negative. Hence, negative spatial spillover tends to worsen the AD. The effects of negative spillover on the AD are more detrimental in the models employing matrices W2 and W3 than W1 and W4. Note that, when W2 and W3 are employed, each team is spatially dependent on only a few teams. However, when W1 and W4 are employed, all teams experience mutual outward and inward spillovers.

Next, if $\rho > 0$, the ratios are usually, but not always, less than one. For the spatial models employing W1 and W4, the ratios are less than one and continue to decline as ρ rises. When W2 and W3 are employed, the ratios are less than one only if ρ is relatively small, but greater than one at larger values of ρ. The results for $N = 20$ (presented in the lower panel) are qualitatively similar to those reported for $N = 10$, but the impact of spillover on AD is somewhat less.

In summary, the numerical simulation results presented in Table 11 suggest that the effects of attendance spillover on CB depend on the direction of spillover, and the magnitude and structure thereof. If the spatial weight matrices are sparse (W2 and W3), spillover tends to compromise AD. However, if the spillover structure lacks a cutoff (W1 and W4), the effects of spillover on AD depend on the sign of the spillover direction.

Next, we explored how sensitively spillover affects AD in the context of the extent of attendance heterogeneity. We compare different levels of attendance disparity between the neighbours. We first consider the case of the minimum attendance difference (market size) between two neighbouring teams. We reset $y_i(= \alpha + u_i)$ in ascending order so that the difference between y_i and y_{i+1} is minimized for any i. We refer to this case as a "small market disparity" among neighbours. The second case redistributes y_i to maximize the attendance difference between the next two neighbours; we term this a "large market disparity". In Tables 12 and 13, we compare the differences between the average attendance standard deviations obtained using the non-spatial and the spatial models with $N = 10$ and 20, respectively in terms of the small and large market disparities, respectively. The results differ substantially from those of Table 11, except for the spatial model employing W1 (with equal weights); the results are then invariant.[8] The upper panel deals with homogenous neighbours with small market disparities. A negative (positive) ρ improves (worsens) AD when the spillover structure is sparse (W2 and W3). The spillover effects on AD are rather

Table 12. Comparison of standard deviations of attendance in non-spatial and spatial models: Different distributions of attendance among neighbours and $N = 10$.

ρ	−0.5	−0.3	−0.1	0.1	0.3	0.5
			Small market disparity among neighbours			
w_1	1.059*	1.034	1.011	0.989	0.968	0.947
w_2	0.789	0.850	0.940	1.072	1.272	1.593
w_3	0.773	0.829	0.930	1.086	1.332	1.758
w_4	0.874	0.916	0.940	1.034	1.115	1.215
			Large market disparity among neighbours			
w_1	1.059	1.034	1.011	0.989	0.968	0.947
w_2	0.960	0.961	0.981	1.026	1.111	1.269
w_3	1.591	1.218	1.043	0.980	1.011	1.168
w_4	1.080	1.037	0.981	0.995	0.996	1.015

Note: *Standard deviation in spatial model in Eq. (4)/standard deviation in non-spatial model in Eq. (3).

[8]Note that the results obtained when employing W1 do not change because W1 assumes that all member teams are neighbours and all paired combinations exhibit equal spillover strengths.

Table 13. Comparison of standard deviations of attendance in non-spatial and spatial models: Different distributions of attendance among neighbours and $N = 20$.

ρ	−0.5	−0.3	−0.1	0.1	0.3	0.5
			Small market disparity among neighbours			
w_1	1.027*	1.016	1.005	0.995	0.984	0.974
w_2	0.720	0.804	0.922	1.095	1.362	1.830
w_3	0.714	0.795	0.918	1.100	1.388	1.898
w_4	0.811	0.875	0.922	1.052	1.180	1.351
			Large market disparity among neighbours			
w_1	1.027	1.016	1.005	0.995	0.984	0.974
w_2	0.930	0.943	0.975	1.034	1.146	1.369
w_3	1.621	1.227	1.044	0.982	1.028	1.230
w_4	1.035	1.011	0.975	1.005	1.029	1.082

Note: *Standard deviation in spatial model in Eq. (4)/standard deviation in non-spatial model in Eq. (3).

sensitive to changes in ρ. For example, if the spillover structure is given by W3, AD improves by 22.7% with $\rho = -0.5$, but worsens by 75.8% with $\rho = 0.5$. The spatial model employing W4 yields a pattern similar to those of models employing W2 and W3, but the impacts are less sensitive to changes in ρ. The results reported in the lower panel (which deals with heterogeneous neighbours with large market disparities) are not unlike those of Table 11. For the spatial model employing W3, the spillover effects on AD follow a U-shape; negative spillover worsens AD more substantially than does positive spillover.

Consider the spatial model employing W3; this assumes that there is/are only one or two neighbours. A positive spillover between any two homogenous neighbour teams (for example, the top two teams with respect to attendance) renders the attendances of these two teams remote from the attendances of other teams. Thus, AD worsens as ρ becomes more positive. On the other hand, a negative spillover moves the attendances of the two teams in opposite directions; AD improves as ρ becomes more negative. Now, deliver a positive random shock to the team with the largest attendance whose only neighbour is the second largest team. If the spatial spillover is positive, the shock raises the attendance of the second largest team, but does not directly impact the attendances of other teams.[9] Thus, the overall standard deviation of league attendance increases. On the other hand, if the spatial spillover is negative, the positive random shock to the largest team reduces the attendance of

[9]The random shock exerts indirect impacts; an attendance change for the second largest team would influence the attendance of the third largest team, and this effect ripples downward.

the second largest team, and the overall attendance standard deviation declines. In the other spillover structures with W2 and W4, changes in AD are not as extreme as those evident when W3 is employed. The results with $N = 20$ (Table 3) are qualitatively similar, but the standard deviation ratios are slightly more sensitive to changes in ρ.

In sum, if neighbours are homogenous in terms of market size, negative (positive) spatial spillovers improve (worsen) the AD. On the other hand, if neighbours are heterogeneous, the impact of spatial spillover on attendance variations is significantly less. This suggests that the impact of spillover on the AD may be sensitive to the attendance distributions among neighbours. Merging the numerical simulations and the positive estimates of SAR coefficients allows the evaluation of the impacts on attendance disparity. For example, the distance weight and the size of Serie A are similar to those of W4 and $N = 20$, respectively. Referring to Tables 5 and 11, the preference change causing spatial spillover in 2013–2016 mildly reduced the attendance disparity by about 1% in standard deviation of the attendance.

Concluding Remarks

We address an important issue: Have neighbour spillover effects influenced Serie A attendances from 2001/02 to 2016/17? We perform spatial panel-data modelling and simulate the impact of attendance spatial spillover on the attendance disparity and eventually CB. Our principal empirical findings are summarized as follows: First, we find no significant spatial interaction effects during earlier seasons (2001–2013) but modest spatial spillovers from 2013 to 2016. These findings are robust across the three different weight matrices employed, the inverse distance-based, the dynasty-based and the shared market-based spatial weight matrices. Second, the estimation results suggest that the indirect effect of HWIN is positive and significant. This implies that win performance has a (slightly) larger effect on attendance in recent periods (2013–2016). Third, Durbin spillover of HGOAL is statistically significant only in shared-markets and particularly, negative spillover implies substitutability with respect to cross-quality among neighbours. Fourth, spatial attendance spillover may significantly affect the attendances of member teams (and thus the distribution of attendance) either positively or negatively. The final outcome depends on the sign of the spatial spillover, the network structure, and the market size distribution among neighbours.

These results have several important implications. Mills *et al.* (2016) and Henrickson (2012) present empirical evidence that multiple teams in a city, or teams otherwise in proximity in North America, influence fan demand and ticket prices. These are simultaneously determined and become equilibrated. Significant cross-quality demand elasticity is apparent. Henrickson (2012) found that a neighbour effect increases the ticket prices. On the other hand, we find that the spatial interaction within Serie A has generally been insignificant, which may reflect strong fan loyalty. Unlike North America, where the major professional sports leagues include baseball, football, basketball, and ice-hockey, Europe features football only. Thus, Serie A may enjoy stronger fan loyalty than North American sports leagues; there is no substitute for Serie A. The demand for home games of a team with strong fan loyalty is likely to be insensitive to changes in demand determinants, including the performance of neighbour teams. Therefore, team spillover may be both unsubstantial and masked by strong fan loyalty.

However, we find empirical evidence of changes in fan preference attributable to neighbour effects in recent seasons. The spatial parameter has become statistically significant since 2013/14. We conjecture that the growing importance of Champion League (CL) may be the principal reason for this preference change, suggesting that in-depth analysis of the dynamics of fan demand would be an important topic for future study. Given the developments in information and communication technologies and transportation, the increasing popularity of the inter-league competition acquaints fans not only with their home teams but also other teams. We also find empirical evidence that there are significant spillover effects of win performance but only within the same city. That is, the cross-quality effect is localized.

These complex spillover structure may influence the attendance distribution across member teams. We combine the SAR estimates with the numerical simulation results to explore the impact of preference change (in terms of spatial spillover) on the attendance disparity since 2013. We find that the impact is sensitive to the market size distribution among neighbours and the direction and magnitude of spatial spillover. The spatial spillover is positive and its magnitude is about 0.1. These findings are robust across the three different weight matrices employed. In spillover structures based on distance or borders, the closest neighbours are teams that share the same city. In general, the market sizes and attendances of teams in the same city are more-or-less homogenous. In this regard, changes in the attendance distribution caused by preference changes since 2013 are apparent in the upper panel of Table 3 with $N = 20$. The fourth column shows that the CB may worsen by a minimum of 5.2% or a maximum of 10%, depending on the spillover structure imparted by the spatial weight matrices W2, W3, and W4. For example, W3 lies close to the shared market spillover structure because any team has only one or two neighbours. If the inward and outward spillovers of fan demand strengthen over time, sports leagues must pay more attention to changes in attendance distribution which may influence CB. For example, if the spillover coefficient is 0.3, the standard deviation of attendance may increase by a minimum of 18% and a maximum of 39%.

Macdonald (2017) stresses that a new generation of panel-data models are required by sports economists who research consumer demand; the models must control unobservable factors such as market competition and various match qualities. Our empirical study is in line with this suggestion, in the sense that we consider not only the absolute and relative qualities of a match but also market competition mediated via spatial effects. Similar empirical studies on spatial spillover in other European football leagues would be interesting. Also, it would be intriguing to examine spatial spillover in North American team sports.

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