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How League Structure Shapes Behaviour: Evidence from Regulatory Changes in Mexico and South Korea

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How League Structure Shapes Behaviour: Evidence from Regulatory Changes in Mexico and South Korea

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Abstract

This paper estimates the causal impact of entry regulation on organisational behaviour and market outcomes by exploiting two natural experiments in professional football. It examines the consequences of transitioning between a promotion-and-relegation system and a closed league in Mexico's *Liga MX* and South Korea's *K-League 1*. Using a difference-in-differences strategy, the analysis compares the evolution of match-level outcomes in the treated leagues with those in suitable control groups—Brazil's *Brasileirão* and Japan's *J-League*. Closing the league in *Liga MX* reduced competitive balance—matches became, on average, less close—lowered stadium attendance by around 40%, and decreased global search interest by about 8 Google Trends points, while also making managerial replacements less effective. Introducing promotion and relegation in the *K-League 1* increased competitive intensity and enhanced the efficacy of managerial changes. Together, these findings provide the first causal evidence on how league design shapes incentives and behaviour in professional sports, with broader implications for industries where performance-based entry rules influence organisational strategy.

JEL Codes: L83, L51, D22, C23

Keywords: Entry regulation, Promotion and relegation, Organisational behaviour, Professional football, Natural experiment, Difference-in-differences

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1 Introduction

When governments lower barriers to entry in an industry, they do not just change who gets to compete—they reshape the entire game: how firms behave, how consumers benefit, and what managers decide. In markets as diverse as air travel, telecoms, and retail banking, entry liberalisation has often triggered changes in pricing, market structure, and firm strategy, typically through increased competition and the emergence of new business models (Goetz and Vowles, 2009; Burghouwt et al., 2015). These examples illustrate a broader economic question: *how do changes in entry regulation affect market outcomes, firm conduct, and the strategic environment in which managers operate?*

This paper exploits two natural experiments in professional association football to evaluate the impact of opening or closing a tournament's structure—specifically, by allowing or prohibiting promotion and relegation—on key industry outcomes such as competitive balance, consumer interest, and managerial decisions. The focus is on policy changes in the top tier of the Mexican league (*Liga MX*), which temporarily suspended promotion and relegation from 2020, and the Korean league (*K-League*), which introduced promotion and relegation for the first time in 2013. The unconventional field of professional sports—association football in particular—offers a fertile setting for assessing the causal effects of entry barriers for at least three reasons. First, unlike most industries where entry regulations are opaque and politically negotiated, football leagues apply entry and exit rules automatically based on on-field performance. Second, the objective function of football clubs—winning matches—and key managerial decisions such as head coach replacements are transparent and publicly observable. Third, match outcomes and spectator engagement metrics—including goals scored, red cards, and stadium attendance—are measured uniformly and reliably across teams and time. These features make football an unusually clean and information-rich environment for studying the consequences of changing entry barriers.

Empirical researchers have evaluated the causal effects of entry regulation across a range of industries, often reporting mixed results. Economides et al. (2008) analyse the deregulation of local U.S. telecommunications markets following the 1996 Telecommunications Act, finding that lowering entry barriers led to increased competition and consumer surplus. In contrast, Briglauer et al. (2018) study EU regulations that required incumbent telecom providers to lease network elements to competitors, and report that such access rules discouraged fibre-optic investment. In financial services, Cornelli et al. (2024) examine the UK's introduction of a regulatory sandbox in 2015, which allowed selected fintech firms to test innovative financial products in a controlled environment. They find that sandbox access improves access to finance and supports entrepreneurship. Barrios et al. (2023) investigate the unintended social effects of platform entry by evaluating how ridehailing services such as Uber and Lyft affected traffic fatalities in U.S. cities. In the education sector, Chen and Harris (2023) assess the impact of the type of authorisation process for charter schools, which is linked both to the number of such schools and to district-wide student outcomes.

Similar tensions emerge in transportation markets. Goetz and Vowles (2009) highlight how U.S. airline deregulation produced large gains in consumer access and affordability, but also led to greater market concentration and volatility in service provision. Burghouwt et al. (2015) document how European air liberalisation fostered the rise of low-cost carriers and new routes, while simultaneously contributing to network consolidation and uneven competition across regions. Taken together, these studies show that the consequences of entry liberalisation are highly context-dependent, shaped by industry structure, strategic responses, and the design of the regulatory framework itself.

To the best of my knowledge, there is no prior causal analysis examining the consequences of opening or closing professional sports leagues. Noll (2002) develops a conceptual framework in which promotion and relegation (P&R) affect club revenues and competitive incentives, thereby encouraging better decision-making and greater investment in player talent. The system may also increase stadium attendance by raising the number of meaningful matches throughout the season. Szymanski and Valletti (2010) build a contest model to analyse how P&R influences clubs' strategic interactions, and provide descriptive evidence that teams near the relegation threshold exhibit distinct patterns of performance. However, in their framework, the threat of relegation is endogenous—it arises from prior outcomes and decisions—so the causal effect of the regulatory regime itself remains untested. Relative to these contributions, the conceptual framework developed here microfounds ex-ante effort with a contest success function and a relegation-survival term and, crucially, embeds a welfare-maximising regulator that trades off total effort against its dispersion, yielding clear comparative statics in the relegation rate and heterogeneous responses across teams.

This study makes three main contributions. First, it provides the first causal estimates of how league structure affects industry outcomes in professional football. Second, it extends the analysis beyond match performance to include managerial behaviour—specifically, head coach replacements—and disciplinary actions, offering a novel perspective on regulation and organisational responses. Third, by evaluating two distinct policy changes across different institutional settings, the study tests the external validity of its findings and assesses their robustness across contexts.

Unlike previous research, this paper estimates the causal impact of transitioning between a promotion-and-relegation system and a closed league on key industry metrics, including match results, managerial decisions, and disciplinary behaviour. The analysis applies a difference-in-differences strategy at the match level to compare the dynamic evolution of these measures in the treated leagues to those observed in appropriate control groups: Brazil's *Brasileirão* for the Mexican case and Japan's *J-League* for the Korean case.

To ensure a valid counterfactual comparison, the analysis of attendance, cards, total goals, and goal differences pairs each treated match with a control observation exhibiting similar pre-treatment values for the outcome variable of interest (see, for example, Abadie and Gardeazabal (2003)). For the analysis of managerial turnover, matches following a head coach replacement are compared with similar matches without a dismissal, where similarity is defined by the extent to which the team's performance up to that point had deviated from betting market expectations (see van Ours and van Tuijl (2016)).

The results indicate that the closure of *Liga MX* to promotion and relegation reduced competitive balance—matches became, on average, about one goal less close—and lowered fan engagement, with stadium attendance falling by around 40% relative to the control league and global search interest declining by roughly 8 Google Trends points. The reform also altered managerial behaviour, with head coach replacements becoming less effective in the short term. Consistently, the introduction of promotion and relegation in the *K-League 1* increased competitive intensity, reduced average goal differences, and enhanced the efficacy of managerial changes, suggesting that open-league structures strengthen performance incentives, organisational responsiveness, and consumer interest. Together, these findings underscore the role of league design in shaping the strategic environment faced by clubs, with broader implications for regulation in sports and other performance-based industries.

The remainder of the paper is structured as follows. Section 2 presents the theoretical framework motivating the empirical analysis. Section 3 describes the institutional context and data sources. Section 4 outlines the empirical strategy. Sections 5 and 6 report the main results and robustness checks. Finally, Section 7 discusses the broader implications of the findings and concludes.

2 Conceptual framework

Consider a two-stage game to study how relegation rules affect team behaviour in sports leagues. In the first stage, the regulator chooses whether to implement relegation, denoted by the binary decision variable $D \in \{0, 1\}$, before teams choose their effort levels. The regulator's objective is to maximise a welfare function that depends positively on the total effort exerted by all teams—interpreted as overall quality—and negatively on the dispersion of effort levels—interpreted as a lack of competitive balance. In stage two, given the regulator's decision, all n teams in the tournament, indexed by $i = 1, \ldots, n$, simultaneously choose non-negative effort levels $e_i \geq 0$ to compete for league success and (if applicable) to avoid relegation.[1]

More formally, in the first stage, the regulator anticipates the teams' best responses in stage two and solves

$$\max_{D \in \{0,1\}} W(D) \;=\; \sum_{i=1}^{n} e_i^*(D) \;-\; \lambda \cdot \mathrm{Var}\big(e_1^*(D), \ldots, e_n^*(D)\big),$$

where $\lambda > 0$ captures the regulator's aversion to unequal effort levels (i.e., a preference for competitive balance).

In the second stage, the payoff of each team i has two components: a fixed reward V for league performance (e.g., prize money, prestige), and a reward R from avoiding relegation (e.g., financial survival, reputation). These parameters are common to all teams and are treated as exogenous. Each team faces a quadratic effort cost,

$$C_i(e_i) \;=\; c_i e_i^2, \qquad c_i > 0,$$

where c_i reflects team i's cost of exerting effort. We assume $c_1 < c_2 < \cdots < c_n$, so that teams with lower c_i—interpreted as stronger or more efficient—face lower marginal costs of effort.

Thus, each team maximises expected utility

$$U_i \;=\; D \cdot \mathbb{P}_i^{\text{stay}} \cdot R \;+\; \mathbb{P}_i^{\text{win}} \cdot V \;-\; c_i e_i^2,$$

where the probability that team i wins is given by a Tullock-type contest success function,

$$\mathbb{P}_i^{\text{win}} \;=\; \frac{e_i}{\sum_{j=1}^{n} e_j}.$$

[1] In contrast to Szymanski and Valletti (2010), which focuses on within-season dynamics where effort is adjusted based on current league position, the approach here examines clubs' strategic decisions at the start of the season—before any match is played and when uncertainty over outcomes is maximal. By modelling effort as an *ex ante* investment, we highlight how the threat of relegation alters incentives across the entire distribution of team strength. This complements the existing literature by showing how league structure shapes initial commitment to performance-enhancing activities such as player recruitment, tactical preparation, and managerial appointments.

If relegation is implemented ($D = 1$), let $r \in (0, 1)$ denote the relegation rate, so that $m = \lfloor rn \rfloor$ teams are relegated. The probability that team i avoids relegation is

$$\mathbb{P}_i^{\text{stay}} = 1 - F_r(e_i; \vec{e}),$$

where $\vec{e} \equiv (e_1, \ldots, e_n)$ and F_r denotes the probability that team i finishes among the bottom m teams. We assume F_r is differentiable, increasing in e_j for $j \neq i$, and decreasing in e_i.

Assumption 1 (Regularity and interiority)**.** For any fixed $D \in \{0, 1\}$ and $r \in (0, 1)$, there exists an interior Nash equilibrium with $e_i^* > 0$ for all i. Moreover, F_r is differentiable with $\frac{\partial F_r}{\partial e_i} < 0$ and $\frac{\partial F_r}{\partial e_j} > 0$ for $j \neq i$, and the marginal benefit of effort is strictly decreasing in e_i (single-crossing).

Proceeding by backward induction, the following lemma characterises the interior second-stage equilibrium.

Lemma 2 (Interior equilibrium characterisation)**.** *Under Assumption 1, any interior Nash equilibrium $\{e_i^*\}$ satisfies, for each i,*

$$2c_i e_i \;=\; \frac{V \sum_{j \neq i} e_j}{\left(\sum_{j=1}^{n} e_j\right)^2} \;+\; D\Big(-\frac{\partial F_r}{\partial e_i}\Big) R.$$

Moreover, equilibrium effort is strictly decreasing in c_i: if $c_i < c_k$, then $e_i^* > e_k^*$.

Proof provided in Appendix A.

Remark 3 (Comparative statics in r and relation to tournament design)*.* The comparative statics with respect to r are analogous to tournament-design results (e.g., Shenkman et al. (2022)): increasing r steepens incentives at the bottom and thus raises equilibrium effort, with the strongest response among high-cost (weaker) teams via the term $\big(-\frac{\partial F_r}{\partial e_i}\big)R$.

Proposition 4 (Effect of relegation on effort)**.** *Fix $r \in (0, 1)$ and parameters V, R, and $\{c_i\}_{i=1}^n$. Let $e^*(D)$ denote the interior equilibrium for $D \in \{0, 1\}$. Under Assumption 1, for any team i,*

$$e_i^*(1) \geq e_i^*(0),$$

with strict inequality whenever $\big(-\frac{\partial F_r}{\partial e_i}\big)\big(e^*(0)\big) > 0$ (i.e., survival probabilities are locally responsive to own effort at the no-relegation equilibrium). Moreover, if teams closer to the relegation cut-off face steeper survival schedules—formally, if $\big(-\frac{\partial F_r}{\partial e_i}\big)$ is weakly larger for higher c_i at $e^*(0)$—then the effort increase $\Delta e_i \equiv e_i^*(1) - e_i^*(0)$ is (weakly) increasing in c_i; hence weaker (high-cost) teams respond more strongly to the introduction of relegation.

Proof provided in Appendix A.

Proposition 4 and Lemma 2 motivate three testable hypotheses regarding the effects of relegation mechanisms in sports leagues. In particular, the model predicts that a stronger threat of relegation leads to a higher equilibrium level of effort across teams. This strategic response may affect match outcomes, player behaviour, and managerial decisions. Specifically, relegation pressure should induce greater prudence in managerial choices—since the downside risk is higher than in a closed league—thereby yielding more effective appointments and improved team performance (Hypothesis 1).

However, the effects on goals and disciplinary cards are a priori ambiguous. On the one hand, greater effort by teams and managers—via enhanced training, tactics, and player selection—may produce more dynamic matches and increase goals scored (Hypothesis 2). On the other hand, higher effort may foster more disciplined play to avoid suspensions, which could reduce yellow/red cards (Hypothesis 3). Conversely, the same mechanisms could tighten defensive organisation and raise physical intensity, potentially lowering goals and increasing cards. Hence the theory does not pin down Hypotheses 2–3 and motivates empirical tests.

Corollary 5 (Effect on competitive balance)**.** *Let $e_i^*(D)$ denote the interior equilibrium effort of team i under $D \in \{0,1\}$, and define $\Delta e_i \equiv e_i^*(1) - e_i^*(0)$. Suppose that efforts are ordered $e_1^*(0) \geq \cdots \geq e_n^*(0)$ (equivalently, $c_1 < \cdots < c_n$) and that the introduction of relegation compresses pairwise gaps in the sense that, for all $i < k$,*

$$0 \;\leq\; \Delta e_k - \Delta e_i \;\leq\; e_i^*(0) - e_k^*(0),$$

with at least one strict inequality. Then the cross-sectional variance of effort falls:

$$\mathrm{Var}\big(e_1^*(1), \ldots, e_n^*(1)\big) \;<\; \mathrm{Var}\big(e_1^*(0), \ldots, e_n^*(0)\big).$$

In particular, this holds if weaker (high-c_i) teams experience (weakly) larger effort increases and no pairwise gap widens.

Proof provided in Appendix A.

According to Corollary 5 and Proposition 4, introducing relegation increases competitive intensity, leading to closer matches and smaller goal differences (Hypothesis 4). Moreover, by increasing both effort and competitive balance, relegation should enhance consumer interest, potentially reflected in higher stadium attendance (Hypothesis 5).

Theorem 6 (Regulator's implementation of relegation)**.** *Let $e_i^*(D)$ denote interior equilibrium efforts under $D \in \{0,1\}$ and $W(D) = \sum_{i=1}^{n} e_i^*(D) - \lambda \,\mathrm{Var}\big(e_1^*(D), \ldots, e_n^*(D)\big)$ with $\lambda \geq 0$. Under Assumption 1, if (i) $e_i^*(1) \geq e_i^*(0)$ for all i with at least one strict inequality (Proposition 4), and (ii) $\mathrm{Var}(e^*(1)) \leq \mathrm{Var}(e^*(0))$ with at least one strict inequality (Corollary 5), then*

$$W(1) \;>\; W(0).$$

In particular, if $\lambda > 0$ and the variance strictly falls, or if $\lambda = 0$ and total effort strictly rises, the regulator optimally chooses $D = 1$.

Proof provided in Appendix A.

While the theoretical incentives to implement an open league structure are clear from the point of view of the regulator, this is not always the case in practice. In reality, such an outcome may fail to constitute a stable Nash equilibrium if teams—particularly those facing higher costs—have the ability and incentive to lobby the regulator in favour of closed-league arrangements that shield them from the risk of relegation. Thus, institutional constraints and political economy considerations may prevent the implementation of welfare-maximising reforms, even when they are desirable in theory.

3 Institutional Context and Data Description

3.1 Liga MX and the Closed League Reform

Liga MX, traditionally structured with promotion and relegation, transitioned to a closed league system in 2020. This decision was taken primarily to help clubs cope with the financial difficulties caused by the COVID-19 pandemic (ESPN, 2023). By eliminating promotion and relegation, the league aimed to provide greater financial stability and to encourage long-term planning among clubs. Mirroring the American franchise model, this reform removed the risk of relegation, allowing teams to prioritise development without the immediate threat of losing their top-tier status.

Liga MX operates with two tournaments per year: the *Apertura*, which runs from July to December, and the *Clausura*, from January to May. Each tournament follows a single round-robin format, with every team playing 17 matches. Although the regular season is followed by playoffs (*Liguilla*) and reclassification matches (*Repechaje*), the analysis focuses exclusively on regular-season matches between 2016 and 2024, encompassing four seasons before and after the policy change.

To evaluate the effects of this reform, I use matches from Brazil's top-tier league, the *Campeonato Brasileiro Série A* (hereafter *Brasileirão*), as a control group. Brazil and Mexico rank among the most competitive football markets in Latin America, with comparable levels of commercial investment, fan engagement, and international visibility. For example, in 2023, the *Brasileirão* attracted an average attendance of over 26,500 spectators per match, placing it among the top seven domestic leagues worldwide, while *Liga MX* has consistently led attendance charts across Latin America.[2] Both leagues feature well-established club brands, major media contracts, and active player export markets. Unlike *Liga MX*, however, the *Brasileirão* maintained a stable promotion and relegation structure throughout the 2016–2024 period, making it a suitable benchmark to isolate the effects of removing relegation.

The *Brasileirão* follows a European-style format: from 2016 to 2024, 20 teams competed in a double round-robin system, playing 38 matches per season (home and away against each opponent). The team with the most points is crowned champion, while the bottom four are relegated to *Série B*. This structure has remained unchanged since 2003. Importantly, there are no playoff or reclassification stages, so all matches are part of the regular season. To ensure comparability with the *Liga MX* sample, I restrict the analysis to regular-season matches in both leagues over the same period.

While identifying a suitable control group is important, the key comparison is conducted at the match level, pairing matches with similar pre-treatment behaviour of the outcome variable. For both countries, I collected match-level data on team characteristics, scores, cards, stadium capacity, attendance, and head-coach attributes from https://www.worldfootball.net/. Additional information on pre-match outcome probabilities was obtained from https://www.oddsportal.com/. [3]

[2]See, for example, https://en.wikipedia.org/wiki/Campeonato_Brasileiro_SÃĨrie_A and https://en.wikipedia.org/wiki/Sport_in_Mexico.

[3]Bookmaker odds are quoted in decimal or fractional form. I convert fractional odds a/b to decimal as $o = a/b + 1$, and I compute implied probabilities as $\tilde{p}_i = 1/o_i$ for $i \in \{\text{home}, \text{draw}, \text{away}\}$. Because odds include a margin, these raw probabilities sum to $R = \sum_i \tilde{p}_i > 1$; I remove the overround by normalising $p_i = \tilde{p}_i / R = \dfrac{1/o_i}{\sum_j 1/o_j}$ so that $p_{\text{home}} + p_{\text{draw}} + p_{\text{away}} = 1$. When odds are missing or cannot be parsed, I estimate an ordered probit for the three outcomes using pre-match covariates and use the fitted $\hat{p}_i$ to

To avoid bias introduced by crowd restrictions, all matches affected by the COVID-19 pandemic were excluded from the attendance analysis. In the case of *Liga MX*, the 2020 calendar year comprised two tournaments: the concluding stage of the *Clausura 2019/2020*, which was suspended and ultimately cancelled, and the beginning of the *Apertura 2020/2021*, which resumed under strict public health protocols, with most matches played behind closed doors. The *Clausura 2020/2021* was likewise heavily affected by limited or no attendance. Consequently, the 2020 and 2021 seasons were excluded for both Mexico and Brazil to ensure consistency and to mitigate pandemic-related disruptions.

Other than the temporary suspension of promotion and relegation in *Liga MX* beginning in 2020—which effectively rendered the league closed during our study window—neither the *Brasileirão* nor *Liga MX* underwent changes to the *regular-season* competition format between 2016 and 2024 that would affect the estimation sample. One postseason reform in *Liga MX* is worth noting: the expansion of the *Liguilla* from eight to twelve qualifiers (via a *repechaje* round, later a play-in format). Under the model in Section 2, this adjustment shifts the qualification margin (from eighth to twelfth) without materially altering the core *match-level* incentives—winning the competition or, in Brazil (and in Mexico before 2020), avoiding relegation. Although this constitutes only a minor change, as a robustness check I control for league-specific trend components in the analysis (see Section 5.5).

Table 1 presents summary statistics for matches in *Liga MX* and the *Brasileirão*. The dataset includes 2,250 matches from *Liga MX* and 3,419 matches from the *Brasileirão*, excluding 396 and 760 matches respectively due to COVID-related restrictions. The two leagues appear broadly comparable in terms of average attendance, disciplinary records (cards), goals scored, and ex-ante match outcome probabilities. The final row reports descriptive statistics for the Google Trends Index, which captures global search interest in each league on a 0–100 scale and will be used in the subsequent analysis; unlike the other variables, these values are not match-level observations but weekly indices covering the 2016–2024 period.

3.2 K-League Structure and Transition to an Open League

The *K-League* is the top tier of professional football in South Korea. From its inception in 1983 until 2012, it operated as a closed league with no formal system of promotion or relegation. Over time, the number of participating teams gradually increased, and the league experimented with various formats, including split seasons and playoff systems to determine the champion. Matches were scheduled according to a national calendar, and final standings were often influenced by post-season performance. As in the case of *Liga MX*, the analysis focuses exclusively on regular-season matches.

In 2013, the *K-League* underwent a major structural reform with the introduction of a two-division system: *K-League 1* and *K-League 2*. This reform marked the official transition to an open league format with promotion and relegation between tiers. The changes aimed to enhance competitive balance, increase fan engagement, and align South Korean football more closely with international standards. Under the new system, the bottom-ranked team(s) in *K-League 1* face relegation to *K-League 2*, while the top team(s) in *K-League 2* are promoted. This shift introduced stronger incentives for performance

impute the missing probabilities.

throughout the season, especially for teams near the relegation zone, and has been central to ongoing efforts to improve the quality and integrity of the domestic league.

The analysis covers the period 2010–2016, comprising three seasons before and four seasons after the transition.[4] Japan's J1 League is used as a control group due to its geographical and cultural proximity. The J1 League operated as an open league with promotion and relegation throughout the entire study period.

Within the study window, apart from the 2013 transition already described, structural adjustments were limited. In South Korea, the top division adopted a late-season "split" after 33 rounds (*Final A/B*) for five additional fixtures. In Japan, the *J1 League* remained an open league throughout but briefly reintroduced a two-stage regular season with a championship play-off in 2015–2016, before returning to a single-stage format in 2017. These institutional details do not affect the definition of the regular-season sample and are reported here for completeness. Nonetheless, Section 5.5 controls for league-specific trend components in the analysis.

Table 2 presents descriptive statistics for matches in the *K-League* and Japan's J1 League, focusing on key match-level variables such as attendance, disciplinary indicators, goals, and ex-ante outcome probabilities computed as in the previous section. Overall, attendance levels are substantially higher in the J1 League, with a mean of 17,428 compared to 8,943 in the *K-League*. This difference persists despite comparable average stadium capacities, suggesting stronger spectator engagement in Japan. However, the two leagues exhibit broadly similar patterns in disciplinary indicators (with a low incidence of red cards relative to Western competitions), goals, and the distribution of match outcome probabilities.

4 Empirical Approach

4.1 Matching Strategy

To ensure a valid counterfactual comparison in the Difference-in-Differences (DiD) analysis of attendance, cards, total goals, and goal difference, I construct for each match a matched sample of treated and control observations based on the pre-treatment values of the outcome variables. Specifically, a Mahalanobis distance matching procedure is implemented using data from the pre-policy seasons (2010–2012), comparing matches in the treated and control groups.

As discussed in the previous section, I rely on two match-level datasets. The first covers the 2016/2017–2023/2024 seasons for *Liga MX* (treated group) and the *Brasileirão* (control group). The second covers the 2010–2016 seasons for *K-League 1* (treated group) and the *J1 League* (control group). In the Mexico–Brazil sample, *Liga MX* implemented its closed-league reform beginning in 2020/2021; all subsequent seasons are considered post-treatment. In the Korea–Japan sample, the *K-League* transitioned to an open league in 2013. To maintain comparability of coefficient signs across samples, I employ a reverse-coded post indicator in the Korea–Japan specification: seasons prior to 2013 are coded as post-treatment and seasons from 2013 onward as pre-treatment (i.e., $Post_t = 1$ for $t < 2013$ and 0 otherwise).

The outcome variables include the natural logarithm of attendance, ln(Attendance),

[4]The analysis begins in 2010, as detailed information on key variables—such as attendance and head coach characteristics—is not consistently available for 2009.

total cards, goal difference, and total goals. Following best practices in causal inference, I perform matching on the outcome variable itself during the pre-treatment period (Abadie and Gardeazabal, 2003; Abadie et al., 2010; Arkhangelsky et al., 2021). Nevertheless, the empirical strategy departs from that literature in two important respects. First, this research exploits the availability of detailed match-level data and incorporates a set of match fixtures fixed effects, which enables the treatment effect to be identified within each match. Second, unlike synthetic control methods that construct a weighted combination of control units to replicate the pre-treatment trajectory of the treated group, this design matches directly at the individual fixture level. Because many matches disappear in the post-treatment period due to relegation, it is not feasible to build a synthetic sample by weighting matches across seasons. Instead, the pre-treatment value of the outcome (e.g. ln(Attendance) in the attendance analysis) is used as the matching covariate. [5]

One-to-one season-by-season matching without replacement is applied. For each treated unit in a given pre-treatment season, the control unit with the smallest Mahalanobis distance based on the relevant outcome variable is identified. After matching, only the post-treatment observations corresponding to the matched fixture pairs are retained. This approach ensures temporal consistency and preserves the integrity of the comparison groups.

The final matched dataset includes: (i) treated–control pairs from the pre-treatment seasons; (ii) the corresponding post-treatment matches involving the same fixtures; (iii) indicators for treatment status and post-treatment period; and (iv) additional covariates relevant to each fixture. This dataset serves as the basis for the main DiD estimation.

4.2 Difference-in-Differences Specification

Based on the matched database described in the previous section, I apply a Difference-in-Differences (DiD) framework to estimate the impact of the policy intervention on four outcome variables: attendance, total cards, total goals, and goal difference. For robustness, two separate specifications are estimated.

In the first model, the treated league is *Liga MX*, which transitioned to a closed league starting from the 2020/2021 season. The Brasileirão, which remained open throughout the analysis period, serves as the control group. In the second model, the treatment group comprises matches in *K-League 1*, which transitioned from a closed to an open league in 2013. The control group consists of matches in the J1 League, which did not undergo any structural reform. In this latter case, the treatment occurs at the beginning of the observation window, resulting in a reversed DiD structure. Regardless of specification, estimation is based on the following equation:

$$\ln(Y_{ijt}) \;=\; \alpha + \gamma_i + \delta_1\,\text{Treatment}_j + \delta_2\,\text{Close}_t + \delta_3\,(\text{Treatment}_j \times \text{Close}_t) + \mathbf{X}'_{ijt}\boldsymbol{\beta} + \varepsilon_{ijt}. \tag{1}$$

where $\ln(Y_{ijt})$ denotes the outcome of interest for fixture i, competition j, and season t (i.e., ln(Attendance), total cards, goal difference, or total goals); γ_i are fixture fixed effects; Treatment_j equals 1 for the treated league and 0 otherwise; Close_t equals 1 in closed-league seasons and 0 otherwise; $\text{Treatment}_j \times \text{Close}_t$ is the interaction term of

[5] I do not match on covariates, since this does not ensure parallel pre-treatment trends in the outcome variable, which is the key requirement for causal identification in a DiD framework.

interest (the DiD effect); $\mathbf{X}_{ijt}$ is a vector of time-varying covariates; and ε_{ijt} is an error term.[6]

To maintain interpretational consistency across the two cases, I define the "closed" period as the seasons before 2013 in the *K-League*, and as the seasons from 2020/2021 onward in *Liga MX*. In both cases, outcomes are compared to those in a league that remained open throughout the period of analysis.

The coefficient δ_3 identifies the average treatment effect of the policy, under the assumption of parallel trends between the treated and control groups.

To assess the plausibility of this assumption, I conduct a pre-trend (placebo) test using only pre-treatment data: seasons prior to 2020/2021 for *Liga MX* and seasons after 2013 for the *K-League*. In the latter case, no treatment is implemented for either group during the placebo window, making it suitable for testing baseline trend comparability. The following regression is estimated:

$$\ln(\mathrm{Y}_{ijt}) = \alpha + \mathbf{Z}'_{ijt}\boldsymbol{\beta} + \sum_{y=1}^{T-1} (\theta_y \mathrm{Year}_y + \phi_y(\mathrm{Treatment}_j \times \mathrm{Year}_y)) + \varepsilon_{ijt} \tag{2}$$

where Year_y are year dummies for each pre-treatment season, and $(\mathrm{Treatment}_j \times \mathrm{Year}_y)$ are their interactions with the treatment group indicator. The coefficients ϕ_y capture whether there are systematic differences in trends between treated and control groups prior to the policy intervention.

To avoid eliminating potentially informative variation, I adopt a conservative specification and *do not include fixture fixed effects* in the pre-trend test. This modelling choice allows divergence in attendance trajectories to be detected, even if driven by specific fixture-level patterns. If the ϕ_y coefficients are jointly statistically insignificant, the null of parallel trends cannot be rejected, thereby supporting the validity of the DiD strategy.

Given that the conceptual framework developed in Section 2 predicts that the impact of closing a tournament is mainly driven by widening the effort (quality) gap between stronger and weaker teams, I also report results for a subsample consisting of matches in which both teams were of low quality—defined as averaging fewer than 1.5 points per game, i.e. matches satisfying $\mathrm{PPG} \leq 1.5$ and $\mathrm{PPG}_{\mathrm{away}} \leq 1.5$—to account for potential performance-based heterogeneity.

4.3 Analysis of Managerial Turnovers

Unlike match-level outcomes such as attendance, cards, total goals, and goal difference, head-coach replacements are managerial choices that should be evaluated against otherwise similar teams in the same league that do not replace their coach. I follow van Ours and van Tuijl (2016) to study how the reform affected the frequency of managerial turnover and its subsequent impact on team performance. The analysis uses a team–match–level panel (two observations per fixture) to examine tenure duration (hazard of dismissal) and how the consequences of a replacement differ before and after the policy within each league (*Liga MX* and *K-League*).

To analyse managerial survival, I estimate a Weibull Accelerated Failure Time (AFT) model using data from *Liga MX* and the *K-League*. Covariates include recent performance

[6] The demeaned (within) regressions absorb fixture fixed effects by subtracting the fixture mean from each variable. Any regressor that is constant within a fixture (e.g., $\mathrm{Treatment}_j$) has zero within-variation after this transform and is therefore not identified. The DiD effect is identified from within-fixture changes in Close_t and is captured by the coefficient on $\mathrm{Treatment}_j \times \mathrm{Close}_t$ (the variable `diff_in_diff`).

(measured as points obtained in the last four matches), managerial nationality, cumulative surprise, and a structural break indicator capturing the policy change.

To evaluate the impact of managerial changes on team performance, a managerial change is identified whenever the identity of the manager differs from that in the previous match within the same season—excluding first matches. For each team-season, only the first managerial change is retained to avoid multiple treatments per unit.

Following van Ours and van Tuijl (2016), to construct a control group each treated team-season (experiencing a managerial change) is paired with a match of the same team in a different season in which no managerial change occurred. Matching is based on cumulative surprise—defined as the difference between observed and expected points from the betting market—calculated up to the point of the actual change. This procedure ensures comparability in team trajectories prior to the intervention (real or placebo) and allows estimation of the causal effect of managerial changes by comparing post-treatment performance between treated and control observations.

To assess the short-term effects of changing the head coach, I again follow van Ours and van Tuijl (2016) and estimate ordinary least squares (OLS) regressions with three dependent variables: goal difference, match victory, and points earned. Covariates include a home-match indicator, average cumulative points prior to the match, and dummies for actual managerial changes (`Treatment`), placebo assignments (`Placebo`), and the post-policy period (`New_regime`). The specification also includes interaction terms between `Treatment` and `New_regime`, and between `Placebo` and `New_regime`, together with team fixed effects.

This framework allows testing whether post-change performance differs between actual and placebo managerial changes, and whether these effects vary across policy regimes. Wald tests are conducted to assess the significance of differences between `Treatment` and `Placebo` effects and their interactions with the policy regime.

5 Impact of the Policy on Consumer Interest and Match Outcomes

Figure 1 shows the evolution of key match outcomes in paired fixtures for *Liga MX* (treated group) and the *Brasileirão* (control group), with the 2020/2021 season marking the introduction of the closed-league format in Mexico. For ln(Attendance), the 2020 and 2021 seasons are excluded, as both *Liga MX* and the *Brasileirão* were affected by crowd restrictions during the COVID-19 pandemic.

Similarly, Figure 2 presents the evolution of match outcomes for *K-League 1* (treated group) and the J1 League (control group) from 2010 to 2016, with the 2013 season marking the transition from a closed to an open league structure in Korea. Due to the matching strategy employed, the figure shows that fixtures in the treated and control groups are comparable in terms of the outcome variables in seasons when both leagues operated under an open format.

At first glance, both case studies suggest that closing the league may reduce attendance, while the effects on other variables are less clear. However, these graphical insights rely on mean values and do not account for fixture-level heterogeneity. Non-significant aggregate effects can coexist with significant disaggregated effects because correlations or treatment effects measured at the aggregate level need not reflect those at the individual or subgroup level. This is the classic problem of "aggregation bias" (Garrett, 2003) or "ecological correlation" (Robinson, 1950), whereby aggregate correlations are driven by between-group variation and can differ substantially—and even in sign—from individual-level associations. In the present context, heterogeneity across matches may yield significant effects within specific subgroups that average out to a non-significant effect when aggregated. Similar considerations are emphasised in epidemiological research by Curran and Bauer (2011), which shows how aggregation can mask or distort underlying relationships. The following sections provide a more rigorous analysis of the policy's impact on each of the key outcome variables at the match level.

5.1 Did the Transition Impact Consumer Interest?

Table 3 reports the results from difference-in-differences estimations with match fixture fixed effects, comparing log attendance in *Liga MX* (treated) and the Brasileirão (control) around the 2020 policy change. Two models are presented: one using the full sample, and another restricted to matches involving low-performing teams (both teams having fewer than 1.5 points per game).

In the full sample, home team performance (*ppg*) is a statistically significant predictor of attendance at conventional levels. Other explanatory variables, such as team size (average performance over the previous five seasons) and differences in winning probabilities, are not significant once fixture fixed effects are included. The DiD coefficient—the main parameter of interest—indicates a statistically significant negative treatment effect of approximately -0.48 (p-value < 0.05), suggesting that the introduction of the closed-league format in *Liga MX* was associated with a decline in attendance of about 38% ($e^{-0.48} - 1$) relative to the control group. The F-test for pre-trends strongly supports the parallel trends assumption in the full sample (p-value $= 0.997$).

The restricted sample of matches between low-performing teams yields consistent results. The estimated DiD effect remains negative and statistically significant, with a larger magnitude of about -0.68 and no evidence of a significant pre-trend. These findings are robust across specifications with and without covariates.

Since stadium attendance may not fully capture all dimensions of consumer interest, a robustness exercise uses Google Trends data on worldwide search interest for *Liga MX* and *Brasileirão* between January 2016 and July 2024. The Google Trends index ranges from 0 to 100, where 100 corresponds to the peak search volume during the sample period. Weekly data were extracted separately for each league and merged into a balanced panel to assess whether global search activity for *Liga MX* declined relative to the Brasileirão following the closure of the league to promotion and relegation. Figure 3 depicts the evolution of the Google Trends indices for both leagues.

For this analysis, I estimate the following model:

$$y_{it} = \alpha + \delta\ \texttt{treated}_i + \gamma\ \texttt{post}_t + \beta\ (\texttt{treated}_i \times \texttt{post}_t) + \mathbf{X}'_{it}\boldsymbol{\theta} + \varepsilon_{it}, \tag{3}$$

where y_{it} is the Google Trends index for league i at time t; `treated` is an indicator equal to one for *Liga MX* and zero for the *Brasileirão*; and `post` equals one from May 2020 onwards, when *Liga MX* was officially closed to promotion and relegation. The interaction term `treated` $\times$ `post` captures the difference-in-differences (DiD) estimator β. The vector $\mathbf{X}'_{it}$ includes month and year fixed effects (or year and week-of-year fixed effects in alternative specifications).

Table 4 presents the estimation results. Across the main specifications, the DiD coefficient $\hat{\beta}$ is consistently negative and statistically significant at the 5% level in the levels specifications, and significant at the 10% level in the log specification. The estimates indicate that, following the closure of *Liga MX* to promotion and relegation, global search interest for the league declined by approximately 8 Google Trends points relative to the *Brasileirão*, holding seasonal patterns constant. [7]

A placebo test using a fictitious treatment date in 2018 yields an insignificant effect, suggesting that the observed decline is unlikely to be driven by pre-existing differences in trends. Overall, the results support the conclusion that the abolition of promotion and relegation reduced international interest in *Liga MX*.

The analysis of consumer interest is confined to *Liga MX*. This restriction stems from corruption episodes in the *K-League 1*, involving 19 fixed matches during the 2010 season and 2 in 2011 across both league and cup competitions. Although these incidents affected only a negligible share of total matches, they had a substantial impact on consumer interest, as reflected in stadium attendance figures. Consequently, it is not possible to fully disentangle the effect of the league's opening from that of the corruption scandal. For this reason, the causal analysis of stadium attendance in the *K-League 1* is presented in the appendix.

Nevertheless, Table A1 shows that the main findings are consistent with the difference-in-differences estimation comparing log attendance in *K-League 1* (treated) and the Japanese J1 League (control) around the 2013 policy change. In the full sample, the DiD coefficient indicates a statistically significant negative treatment effect of approximately -0.20 (p-value < 0.05). Moreover, Figure A1 in the appendix illustrates that attendance was markedly lower in the *K-League 1* during the period it operated as a closed league. The estimated DiD coefficients remain negative and statistically significant in the full sample, although the effect weakens in the low-performance subsample.

A further robustness check recognises that, although the open-league format with two divisions was officially implemented in 2013, the transition began in 2012. Table A3 reports DiD results for the natural logarithm of match attendance, excluding the 2012 season. The estimates, which include all observations and covariates, are qualitatively similar to the main results, although not statistically significant.

5.2 Did the transition affect the number of cards?

Table 5 presents the results of the difference-in-differences estimations comparing the total number of cards per match in *Liga MX* (treated group) and the *Brasileirão* (control group), around the 2020 policy change. Regression covariates include club history and stadium capacity, as these may influence the level of aggression in a match. Across all specifications, the estimated coefficients for the interaction term `diff_in_diff` are statistically insignificant in the full sample and vary in sign depending on the specification. These findings suggest that there is no clear evidence that the transition to a closed league format in Mexico systematically affected referee behaviour, as proxied by the number of cards shown per match.

Table 6 reports analogous difference-in-differences estimates for South Korea's *K-League 1* (treated group) and Japan's *J1 League* (control group). The results indicate a large and statistically significant increase in the number of cards—approximately four

[7] Google Trends indexes search intensity on a scale from 0 to 100, where 100 corresponds to the maximum weekly search interest observed for either *Liga MX* or *Brasileirão* worldwide during 2016–2024. Thus, an 8-point decline means an 8% drop relative to the peak observed across the sample period, not an absolute count of searches.

additional cards per match—following the transition to an open league format. This increase may reflect heightened competitiveness associated with the reintroduction of promotion and relegation.

Importantly, the pre-trend F-tests reported in the final rows of the table support the identifying assumption of parallel trends, as no significant differences are detected in the pre-treatment period (i.e., post-2013 seasons, due to the reverse DiD setup). Overall, the results suggest a rise in disciplinary actions following the removal of relegation incentives in the K League.

Table A4 presents robustness checks excluding the 2012 season. The estimates are broadly consistent with those in Table 6, reinforcing the robustness of the findings.

Overall, the evidence on the impact of opening the league on the number of cards is mixed. Institutional and cultural factors embedded in each league are likely to play an important role in shaping referee behaviour and team aggressiveness.

5.3 Did the Transition Affect Goal Differences?

Table 7 reports the difference-in-differences estimation results using the absolute goal difference per match as the outcome variable. Covariates capture team differences in history, performance in the current and previous seasons, and stadium capacity.

For *Liga MX*, the DiD coefficient is positive and statistically significant in both the full sample and the low-PPG subsample (though with a smaller magnitude) when covariates are included. Specifically, the full sample yields an estimated DiD effect of approximately 1.49 (p-value < 0.01), suggesting that the introduction of the closed-league system was associated with an increase of about one goal in the average absolute goal difference. In the low-PPG group, the effect is smaller and not statistically significant (coefficient $\approx$ 0.39, p-value $= 0.138$).

In specifications without covariates, the DiD estimates also indicate that a closed league is significantly associated with an increase of around one goal in the absolute goal difference, although statistical significance weakens for the low-PPG subsample. Taken together, these results provide suggestive evidence that the structural reform in *Liga MX* may have reduced competitive balance.

Table 8 presents analogous results for Korea's *K-League* (treated) and Japan's top division (control). Consistent with the findings for Mexico, the closed-league format in Korea is also associated with an increase in absolute goal differences—approximately one additional goal per match on average. Pre-trend F-tests reveal no significant differences in trends between treated and control groups prior to the intervention, supporting the parallel trends assumption. However, as in *Liga MX*, the significant effect is only observed in the full sample; in the low-performance subsample (PPG ≤ 1.5), the interaction term is insignificant at conventional levels.

As shown in Table A5, these results are robust to excluding the 2012 season.

Overall, the evidence suggests that outcome variability is higher under closed-league formats in both *Liga MX* and the *K-League*. Thus, the improvement in competitive balance associated with opening the league appears more evident when the full sample of paired match fixtures—including both stronger and weaker teams—is considered.

5.4 Did the Transition Affect Total Goals?

Table 10 reports the difference-in-differences estimation results using the total number of goals per match as the dependent variable in *Liga MX*. Focusing on the main variable of interest, the difference-in-differences coefficient indicates that a closed-league format is associated with an increase in total goals, although the size of this effect depends on the econometric specification. Specifically, the estimated effect ranges from approximately 0.854 additional goals per match when covariates are included to around 0.783 additional goals in a model with only fixture fixed effects. This pattern is consistent with the hypothesis that removing relegation reduces competitive incentives for struggling teams, which may result in more open matches and higher goal counts (Hypothesis 5).

For the *K-League*, the difference-in-differences estimates reported in Table 10 also indicate an increase in total goals associated with a closed-league format, though the size and statistical significance of this effect vary by specification. Specifically, the coefficient on the interaction term (DiD) is 0.692 ($p = 0.151$), suggesting an increase of less than one goal per match. This effect is robust in the low-PPG subsample and in the specifications without covariates, although it is not statistically significant at conventional levels except in the low-PPG subsample without covariates.

The pre-trend test confirms parallel trends in the full sample (F $=$ 0.00, $p = 1.000$), but detects a significant deviation in the low-PPG subsample (F $=$ 5.11, $p = 0.025$), underscoring the importance of basing causal inference on the full-sample estimation.

Results are qualitatively, and even quantitatively, similar when the 2012 season is excluded, although statistical significance is weaker, likely due to the smaller sample size (see Table A6).

5.5 Further Robustness Analysis

Two complementary robustness exercises are implemented: (i) the DiD specification is augmented with country-specific GDP growth and league-specific linear and quadratic trends; and (ii) all specifications are re-estimated excluding the 2024 season, which displays an unusual decline in absolute goal difference and total goals. Regarding the first concern, as is standard in difference-in-differences (DiD) designs, causal identification in the previous sections rests on treated and control fixtures exhibiting similar pre-treatment trends. A natural concern, however, is that league-specific forces may confound the estimates. In particular, differential economic growth across the treated and control countries could affect stadium attendance and, potentially, on-field outcomes. Other time-varying factors (beyond GDP) may also evolve differently by league.

Accordingly, the DiD specification with fixture fixed effects (and no covariates) is augmented by including (i) country-specific GDP growth and (ii) league-specific linear and quadratic time trends, which flexibly capture slow-moving differences in the evolution of each league (e.g., format changes or macroeconomic conditions affecting the full period).[8]

Identification of the DiD effect in this enriched setting remains challenging. The treatment varies at the league level, and macro indicators such as GDP growth also vary only at that aggregate level. Fixture fixed effects (implemented via demeaning) absorb all time-invariant cross-fixture differences, so identification comes exclusively from

[8] *GDP growth data.* Annual growth rate of real GDP (constant local currency), sourced from the World Bank's World Development Indicators (indicator `NY.GDP.MKTP.KD.ZG`). The sample spans 2010–2016 for Japan and South Korea, and 2016–2024 for Mexico and Brazil. Series were retrieved programmatically via `pandas_datareader::wb` and aligned so that `season` equals the WDI calendar year.

within-fixture changes over time. Introducing a post-treatment indicator further absorbs common time variation shared across leagues. Consequently, there is limited independent variation left to separately identify macro controls while also estimating the DiD interaction, and the latter should be interpreted with caution. In practice, incorporating these controls and trends does not materially alter the substantive conclusions from the baseline specifications (see the tables reported below); rather, it reassures that the results are not driven by simple cross-league macro dynamics.

Table A7 reports DiD estimates for *Liga MX* versus Brazil across the four match outcomes, while Table A8 presents the analogous results for Korea's *K-League* (treated) and Japan's top division (control). Despite the additional noise introduced by macro controls and league-specific trends, the central message holds: closing the league (removing promotion and relegation) is associated with lower attendance. For Mexico, the DiD coefficient on log attendance is large and precisely estimated ($p < 0.001$), implying a reduction of roughly $100 \times (e^{-0.495} - 1) \approx 39\%$. [9] Furthermore, and consistently with the baseline analysis, the DiD estimates for absolute goal difference suggest a deterioration in competitive balance (larger score margins) of the same sign and similar magnitude as in the baseline analysis, but these effects are not statistically significant at conventional levels, reflecting reduced precision in the robustness specification.

The second robustness exercise addresses the sharp reduction in absolute goal difference and total goals observed in 2024 (Figure 1) in *Brasileirão*. Although specifications with fixture fixed effects need not mirror movements in aggregated series, estimates are recomputed excluding the 2024 season as a further test. Tables A9 and A10 summarise the results. Excluding 2024, the association between closing *Liga MX* and higher absolute goal differences remains statistically significant in the full matched sample, confirming the detrimental effect of closing the league for competitive balance. By contrast, the interaction term for total goals (*diff_in_diff*) remains imprecisely estimated and statistically indistinguishable from zero.

6 Did the Transition Affect Decisions on Managerial Change?

Using information from http://www.worldfootball.net, I recorded all within-season managerial changes and collated them with similar information from *Transfermarkt*. I then identified the reason for each change through media sources. Table A11 presents a comprehensive list of all within-season managerial changes in *Liga MX* between the Apertura 2016 and Clausura 2024 tournaments. The majority of replacements appear to be driven by poor sporting performance, although other causes—such as health issues, internal disputes, or the scheduled end of caretaker appointments—are also cited. Notably, certain clubs, such as CD Veracruz and Puebla FC, appear repeatedly, reflecting persistent instability in managerial leadership throughout the observed period. After excluding tournaments affected by the COVID-19 pandemic and dismissals attributed to non-sporting reasons, a total of 64 within-season replacements remain, of which 44 occurred prior to the transition to a closed-league format.

Similarly, Table A12 provides an overview of all within-season managerial changes in the *K-League* between the 2010 and 2016 seasons. Compared to Mexico, and to the norm

[9] While the impact of the policy change in Korea on stadium attendance is contaminated by the corruption scandal, the corresponding effect is even larger (about $100 \times (e^{-1.387} - 1) \approx 75\%$, $p < 0.001$).

in Western football (van Ours and van Tuijl, 2016; Tena and Forrest, 2007), within-season managerial turnover is a rare event in the K-League. In total, only 20 such changes occurred during this period, of which just 12 were performance-related—five before and seven after the league reform.

To investigate the determinants of managerial turnover in both leagues, I estimate a duration model that accounts for the length of each managerial spell within a team-season and whether it concludes with a dismissal. A spell is defined as a continuous period during which a manager leads a team within a given season. The dataset is constructed at the spell level and includes each spell's duration (measured in matches), a binary indicator for whether the spell ended in dismissal, and several managerial and performance-related covariates.

The analysis employs an Accelerated Failure Time (AFT) model with a Weibull distribution to estimate the time until a managerial change occurs for sporting reasons. By comparing model estimates before and after the policy reform, it is possible to assess whether the reform significantly altered the dynamics of managerial dismissals.

Table 11 reports the results of the AFT model for both *Liga MX* and the *K-League*. As shown in Table A13, the results are robust when considering 2012, rather than 2013, as the year of policy change.

Interestingly, foreign managers tend to have shorter tenures in Mexico, while in Korea they remain in charge significantly longer, suggesting potential institutional or cultural differences in managerial stability. Post-policy indicators do not show statistically significant effects on spell duration; however, the positive sign in Korea may indicate a more cautious approach following the league reform. Overall, the findings reveal structural differences in how performance, expectations, and managerial profiles influence tenure across the two leagues, while the reform itself does not appear to have had a substantial effect on spell duration.

Table 12 presents the estimated short-term effects of within-season managerial dismissals (for sporting reasons) on team performance, using three outcome variables: goal difference, probability of victory, and points earned in the immediate subsequent match. Seasons affected by COVID-19 are excluded to avoid biases due to exceptional disruptions.

In the case of *Liga MX*, while the effect varies by outcome variable, the overall results suggest that, prior to the transition to a closed league, teams that replaced their manager performed similarly to placebo teams that—under comparable conditions—did not. However, after the transition, replacing the manager resulted in significantly worse performance than the control group.

The *K-League* exhibits a similar pattern: teams that replaced their managers under a closed-league format experienced more negative short-term outcomes relative to the control group, whereas this effect dissipated after the league reopened. Table A14 re-estimates the results using 2012 instead of 2013 as the year of policy change. Although the results also indicate a more negative impact of managerial replacements prior to the league reopening, the differences between treated and control groups are not statistically significant at conventional levels, likely due to the limited number of treated cases. Nonetheless, even in this case, when comparing the treatment effect before and after 2012, replacing the manager under a closed-league format (prior to 2012) yields a negative and statistically significant effect at the 10% level across all three outcome variables. Once the league reopens, the effect becomes positive and mostly statistically insignificant.

Taken together, and despite institutional and cultural differences influencing managerial turnover in *Liga MX* and the *K-League*, the evidence supports Hypothesis 1: within-season head-coach replacements are more effective in open-league formats.

7 Discussion and Concluding Remarks

This paper has examined the causal impact of transitioning between promotion-and-relegation systems and closed leagues in professional football, using natural experiments in Mexico and Korea. The evidence suggests that opening a tournament to promotion and relegation generally makes the competition more dynamic and engaging. Specifically, it leads to closer matches—approximately one fewer goals of difference on average (Hypothesis 4)—and an increase in the total number of goals scored (Hypothesis 2). Moreover, the shift to an open-league format appears to discipline head coach replacement decisions, making them more efficient in the short term (Hypothesis 1).

The transition also enhances consumer interest (Hypothesis 5), as measured by stadium attendance and Google search activity. However, this effect could be reliably quantified only for *Liga MX*, given that corruption scandals in the *K-League 1* during 2010 and 2011 confound the measurement of consumer interest in the Korean case.

These results have broader implications beyond football. They suggest that the design of entry regulation—particularly the presence or absence of automatic, performance-based rules—can significantly shape the strategic environment in which organisations operate. In sectors where performance is measurable and entry barriers are policy-driven, similar mechanisms may apply. Lowering entry barriers may increase effort levels, especially among incumbents facing a greater risk of being displaced by new entrants. This can improve competitive balance, enhance organisational behaviour, and raise consumer satisfaction with service quality. The analysis also finds evidence of more effective managerial replacement decisions under an open league structure—but only in the case of Liga MX.

Like any empirical study, this analysis has limitations. The findings are drawn from professional football and are not intended to claim universal applicability. Rather, the goal is to provide credible evidence on how entry regulation shapes behaviour in a well-defined, transparent, and information-rich environment. As Giambatista et al. (2005) note, many non-sports studies are also concentrated in specialised sectors—such as manufacturing firms—where generalisability may likewise be limited. In this sense, sports offer distinctive advantages for causal analysis: clear performance metrics, publicly observable managerial decisions, and well-specified institutional rules. These features make professional football a useful laboratory for studying broader questions of regulation and organisational response.

Moreover, the results in this analysis do not imply that a closed industry structure could not constitute a Nash equilibrium in certain contexts. In some cases, incumbent firms may prefer a closed system and lobby regulators accordingly, particularly if the absence of new entrants offers greater financial stability or protects sunk investments. Understanding the trade-offs involved in entry regulation therefore requires careful attention to both efficiency and political economy considerations.

Future research could explore similar policy transitions in other sports leagues or industries, particularly where structural reforms are recent or ongoing. For instance, the U.S. soccer system—historically closed—has seen increasing debate over the introduction of promotion and relegation, fuelled by FIFA pressure and club-level legal challenges. In contrast, China's Super League has recently reintroduced promotion and relegation mechanisms after a period of instability and suspended relegations. The Indian Super

League, initially designed as a closed competition, has gradually incorporated promotion from the I-League since 2022. These cases offer promising grounds to examine whether different institutional settings yield comparable behavioural responses. More broadly, testing the organisational effects of regulatory design across domains—especially where performance metrics are transparent and entry is policy-governed—remains a fertile direction for future research.

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Tables

Table 1: Descriptive statistics for matches in *Liga MX* and the *Brasileirão*

	Liga MX				*Brasileirão*			
Variable	Mean	Std	Min	Max	Mean	Std	Min	Max
Attendance	23049	10957	4651	69486	21545	14830	79	69997
Stadium Capacity	40352	15238	19703	73000	45399	21129	12500	79000
Home Yellow Cards	2.000	1.327	0.000	7.000	2.252	1.427	0.000	10.000
Away Yellow Cards	2.207	1.340	0.000	8.000	2.468	1.476	0.000	9.000
Home Red Cards	0.111	0.337	0.000	2.000	0.073	0.279	0.000	3.000
Away Red Cards	0.119	0.338	0.000	2.000	0.081	0.294	0.000	3.000
Home Goals	1.515	1.225	0.000	9.000	1.395	1.143	0.000	7.000
Away Goals	1.176	1.072	0.000	6.000	0.976	0.985	0.000	6.000
Prob. Away Win	0.288	0.085	0.079	0.535	0.239	0.084	0.066	0.547
Prob. Draw	0.267	0.016	0.182	0.281	0.263	0.021	0.160	0.287
Prob. Home Win	0.434	0.087	0.195	0.682	0.502	0.088	0.294	0.779
Google Trends Index	17.44	10.14	1.00	38.00	22.31	20.80	0.00	100.00

Note: Statistics are based on 2,250 matches in *Liga MX* and 3,419 matches in the *Brasileirão*. Matches affected by COVID-related attendance restrictions are excluded only from the Attendance row. The last row corresponds to the Google Trends Index, which measures relative search interest on a scale from 0 to 100, where 100 is the maximum weekly search interest observed for either league worldwide during 2016–2024.

Table 2: Descriptive statistics for matches in *K-League* and J1 League

	K League				J1 League			
Variable	Mean	Std	Min	Max	Mean	Std	Min	Max
Attendance	8943	8051	763	60747	17428	8648	2104	62632
Stadium Capacity	33663	16263	11000	66806	32473	16556	15165	72327
Home Yellow Cards	1.662	1.160	0.000	7.000	1.313	1.133	0.000	6.000
Away Yellow Cards	1.834	1.235	0.000	7.000	1.451	1.158	0.000	7.000
Home Red Cards	0.024	0.153	0.000	1.000	0.018	0.134	0.000	1.000
Away Red Cards	0.031	0.176	0.000	2.000	0.026	0.163	0.000	2.000
Home Goals	1.421	1.213	0.000	7.000	1.451	1.263	0.000	7.000
Away Goals	1.183	1.100	0.000	6.000	1.264	1.140	0.000	6.000
Prob. Away Win	0.306	0.125	0.082	0.617	0.348	0.099	0.065	0.688
Prob. Draw	0.278	0.021	0.199	0.297	0.246	0.014	0.151	0.256
Prob. Home Win	0.401	0.138	0.124	0.715	0.437	0.109	0.162	0.711

Note: Statistics are based on 1,466 matches in *K-League* and 2,142 matches in J1 League.

Table 3: Difference-in-Differences Estimation Results (Log Attendance): *Liga MX* vs Brasileirão

	All Observations		Low PPG Subsample	
	Coef.	P-value	Coef.	P-value
Panel A: Covariates				
ppg$^{(1)}$	0.296	0.000	0.698	0.011
ppg_away$^{(1)}$	0.091	0.044	0.217	0.012
size$^{(2)}$	-0.026	0.296	0.033	0.511
size_away$^{(2)}$	-0.002	0.955	-0.017	0.803
prob_diff$^{(3)}$	1.656	0.219	0.401	0.923
prob_diff_squared	1.487	0.355	0.320	0.950
post_treatment	0.242	0.000	0.318	0.000
diff_in_diff	-0.482	0.000	-0.676	0.000
Panel B: No Covariates				
post_treatment	0.246	0.000	0.302	0.000
diff_in_diff	-0.489	0.000	-0.693	0.000
AIC	3157.20		1440.51	
AIC (no covariates)	3273.84		1500.23	
Observations	3302		1323	
F-statistic	20.62	0.000	6.97	0.000
F-statistic (no covariates)	61.14	0.000	24.35	0.000
Pre-trend F-test	1.1E-05	0.997	0.476	0.490

Note: All regressions include fixed effects for fixtures and use standard errors clustered at the fixture level. Estimates correspond to OLS models with demeaned treatment (absorbed by fixed effects).
(1) *ppg* refers to points per match.
(2) *size* is a performance-based measure calculated as a weighted average of a team's points per match over the five most recent seasons, giving more weight to recent performance (weights = 1, 1/2, ..., 1/5).
(3) *prob_ diff* is the difference in the ex-ante probability to win the match. Probabilities are obtained from the betting market or, when unavailable, estimated using an ordered probit model.

Table 4: Impact of *Liga MX* Closure on Search Interest (Google Trends Index, 2016–2024)

	Dependent Variable: Google Trends Index			
Specification	DiD Estimate	SE (HAC)	p-value	N
Levels + Month/Year FE	-8.33^{**}	3.76	0.027	216
Levels + Year & WOY FE	-8.33^{**}	3.61	0.021	216
Log(1+Index) + Month/Year FE	-0.46^{*}	0.24	0.055	216
Placebo (2018–07–01)	-4.71	3.26	0.148	216

Notes: HAC standard errors with eight lags. FE = fixed effects. WOY = week of year. $^{**}\,p < 0.05$, $^{*}\,p < 0.10$. The placebo test uses a fictitious treatment date (July 2018) to check for pre-trend bias.

Table 5: Difference-in-Differences Estimation Results (Total Cards): *Liga MX* vs *Brasileirão*

	All Observations		Low PPG Subsample	
	Coef.	P-value	Coef.	P-value
Panel A: Covariates				
home_history$^{(1)}$	0.000	0.878	—	—
away_history$^{(1)}$	0.000	0.878	—	—
average_cumulative_home_points	0.021	0.836	—	—
average_cumulative_away_points	0.115	0.286	—	—
size$^{(2)}$	-0.262	0.073	—	—
size_away$^{(2)}$	0.232	0.154	—	—
var$^{(3)}$	0.374	0.680	—	—
post_treatment	-0.030	0.970	—	—
diff_in_diff	0.321	0.678	—	—
Panel B: No Covariates				
post_treatment	0.254	0.634	0.853	0.372
diff_in_diff	-0.006	0.991	-0.770	0.434
AIC	8950.69		4399.09	
AIC (no covariates)	12910.44		4399.09	
Observations	2091		1263	
F-statistic	1.680	0.102	0.461	0.461
Pre-trend F-test	0.000	0.997	3.127	0.078

Note: All regressions include fixed effects for fixtures and use standard errors clustered at the fixture level. Estimates correspond to OLS models. The dependent variable is the total number of cards per match, where red cards are weighted as two yellow cards.

(1) *home_history* and *away_history* measure the number of months between the club's foundation date and the match date, for home and away teams respectively.
(2) *size* is a performance-based measure calculated as a weighted average of a team's points per game over the five most recent seasons, giving more weight to recent performance (weights $= 1, 1/2, \ldots, 1/5$).
(3) *var* is an indicator equal to one from the 2018 Apertura in *Liga MX* and from the 2019 season in *Brasileirão*.

Additional note 1: In the Low PPG subsample, the estimation with covariates could not be computed reliably because of severe multicollinearity and very limited within-fixture variation. This led to non-invertible cluster-robust variance–covariance matrices, so standard errors and p-values could not be obtained.
Additional note 2: Stadium capacity for home and away teams was included in the regressor set but estimated with very high noise; results are therefore not reported in the table.

Table 6: Difference-in-Differences Estimation Results (Total Cards): *K League 1* vs J1 League

	All Observations		Low PPG Subsample	
	Coef.	P-value	Coef.	P-value
Panel A: Covariates				
home_history$^{(1)}$	-0.017	0.148	-0.082	0.000
away_history$^{(1)}$	0.027	0.015	0.079	0.000
ppg$^{(2)}$	-0.068	0.602	0.169	0.435
ppg_away$^{(2)}$	-0.084	0.499	-0.940	0.000
size$^{(3)}$	0.043	0.756	-0.011	0.965
size_away$^{(3)}$	0.050	0.724	0.576	0.009
post_treatment	-0.946	0.038	0.262	0.238
diff_in_diff	1.840	0.000	0.265	0.233
Panel B: No Covariates				
post_treatment	-1.264	0.002	-5.000	0.000
diff_in_diff	1.726	0.000	5.412	0.000
AIC	5667.89		1606.04	
AIC (no covariates)	7658.79		2004.10	
Observations	489		489	
F-statistic	4.36	0.000	9517.84	0.000
Pre-trend F-test	0.00003	0.996	0.048	0.826

Note: All regressions include fixed effects for fixtures and use standard errors clustered at the fixture level. The dependent variable is the total number of cards per match, where a red card is weighted as two yellow cards.

(1) *home_history* and *away_history* measure the number of months between the club's foundation date and the match date, for the home and away team respectively.
(2) *ppg* and *ppg_away* refer to the average points per game accumulated by the home and away teams at the time of the match.
(3) *size* and *size_away* are weighted averages of performance (PPG) over the previous five seasons, with more recent seasons receiving higher weights $(1, 1/2, \ldots, 1/5)$.

The pre-trend F-test is calculated over post-2013 seasons due to the reverse DiD structure.

Table 7: Difference-in-Differences Estimation Results (Absolute Goal Difference): *Liga MX* vs Brazil

	All Observations		Low PPG Subsample	
	Coef.	P-value	Coef.	P-value
Panel A: With Covariates				
diff_history$^{(1)}$	0.0000	0.045	0.0000	0.384
diff_points$^{(2)}$	-0.001	0.974	0.046	0.489
diff_capacity$^{(3)}$	0.0000	0.041	0.0000	0.677
diff_size$^{(4)}$	-0.017	0.744	0.066	0.469
var	0.773	0.270	-0.569	0.123
post_treatment	-1.434	0.009	-0.268	0.153
diff_in_diff	1.491	0.007	0.301	0.138
Panel B: No Covariates				
post_treatment	-0.859	0.013	-0.857	0.079
diff_in_diff	0.874	0.013	0.846	0.091
AIC	5027.47		1416.02	
AIC (no covariates)	7649.99		2136.07	
Observations	1791		609	
F-statistic	2.155	0.059	0.843	0.499
Pre-trend F-test	0.000	0.980	62.51	0.000

Note: The dependent variable is the absolute goal difference per match. All regressions include fixture fixed effects, with standard errors clustered at the fixture level.

(1) *diff_history* is the difference in club age (in months).
(2) *diff_points* is the difference in average points per game (PPG) at baseline.
(3) *diff_capacity* is the difference in stadium capacity.
(4) *diff_size* is the difference in average performance (PPG) over the previous five seasons.

Table 8: Difference-in-Differences Estimation Results (Absolute Goal Difference): Korea vs Japan

	All Observations		Low PPG Subsample	
	Coef.	P-value	Coef.	P-value
Panel A: With Covariates				
diff_points$^{(1)}$	0.010	0.819	0.099	0.211
diff_size$^{(2)}$	0.109	0.075	0.038	0.677
post_treatment	-0.607	0.011	0.217	0.585
diff_in_diff	0.700	0.005	-0.199	0.644
Panel B: No Covariates				
post_treatment	-0.656	0.012	0.236	0.545
diff_in_diff	0.743	0.006	-0.169	0.691
AIC	3960.14		1134.28	
AIC (no covariates)	5947.97		1558.17	
Observations	1470		493	
F-statistic	2.53	0.041	0.67	0.615
Pre-trend F-test	0.00007	0.993	0.67	0.414

Note: The dependent variable is the absolute goal difference per match. All regressions include fixture fixed effects, with standard errors clustered at the fixture level.

(1) *diff_points* is the difference in average points per game (PPG) at baseline.
(2) *diff_size* is the difference in average performance (PPG) over the previous five seasons, with more recent seasons receiving higher weights $(1, 1/2, \ldots, 1/5)$.

The pre-trend F-test is calculated over post-2013 seasons due to the reverse DiD structure.

Table 9: Difference-in-Differences Estimation Results (Total Goals): *Liga MX* vs Brazil

	All Observations		Low PPG Subsample	
	Coef.	P-value	Coef.	P-value
Panel A: With Covariates				
ppg$^{(1)}$	0.044	0.507	0.260	0.157
ppg_away$^{(1)}$	-0.011	0.886	0.081	0.160
size$^{(2)}$	0.127	0.170	0.110	0.182
size_away$^{(2)}$	-0.104	0.271	-0.073	0.159
var$^{(3)}$	0.154	0.204	-0.226	0.243
post_treatment	-0.838	0.060	-0.472	0.799
diff_in_diff	0.854	0.057	0.745	0.805
Panel B: No Covariates				
post_treatment	-0.706	0.129	-0.626	0.436
diff_in_diff	0.783	0.096	0.764	0.350
AIC	7890.37		2839.03	
AIC (no covariates)	10314.07		3651.56	
Observations	2234		904	
F-statistic	1.340	0.230	0.372	0.587
Pre-trend F-test	0.0003	0.986	0.0142	0.905

Note: The dependent variable is the total number of goals per match. All regressions include fixture fixed effects, with standard errors clustered at the fixture level.

(1) *ppg* and *ppg_ away* are the average points per game accumulated by the home and away teams before the match.
(2) *size* and *size_ away* are weighted averages of performance (PPG) over the previous five seasons, with more recent seasons given higher weights $(1, 1/2, \ldots, 1/5)$.
(3) *var* is an indicator equal to one in seasons when the Video Assistant Referee (VAR) system was in use.

Additional note: Stadium capacity (home and away) and club history (home and away) are absorbed by the fixture fixed effects and therefore not reported in the table.

Table 10: Difference-in-Differences Estimation Results (Total Goals): *K-League 1* vs Japan

	All Observations		Low PPG Subsample	
	Coef.	P-value	Coef.	P-value
Panel A: With Covariates				
history$^{(1)}$	0.003	0.869	0.002	0.686
history_away$^{(1)}$	-0.012	0.482	0.002	0.686
ppg$^{(2)}$	-0.025	0.829	0.105	0.604
ppg_away$^{(2)}$	0.017	0.893	-0.041	0.841
size$^{(3)}$	0.307	0.087	0.111	0.670
size_away$^{(3)}$	-0.035	0.847	0.279	0.225
post_treatment	-0.738	0.152	-0.643	0.437
diff_in_diff	0.692	0.151	0.925	0.126
Panel B: No Covariates				
post_treatment	-0.261	0.575	-1.000	0.000
diff_in_diff	0.515	0.280	1.137	0.000
AIC	5680.26		1746.97	
AIC (no covariates)	7494.13		1994.69	
Observations	1556		551	
F-statistic	1.28	0.255	1.44	0.199
Pre-trend F-test	0.00	1.000	5.11	0.025

Note: The dependent variable is the total number of goals per match. All regressions include fixture fixed effects, with standard errors clustered at the fixture level.

(1) *history* and *history_ away* refer to the age of the home and away clubs (in months).
(2) *ppg* and *ppg_ away* are the average points per game accumulated by the home and away teams before the match.
(3) *size* and *size_ away* are weighted averages of performance (PPG) over the previous five seasons, with more recent seasons receiving higher weights $(1, 1/2, \ldots, 1/5)$.

The pre-trend F-test is calculated over post-2013 seasons due to the reverse DiD structure.

Table 11: Determinants of spell durations in Liga MX and K League. Accelerated Failure Time (AFT) model

	Liga MX			K League		
Covariate	Coef.	Exp(Coef)	SE(Coef)	Coef.	Exp(Coef)	SE(Coef)
Experience	-0.002	0.998	0.007	-0.029	0.971	0.013
Nationality	-0.161	0.851	0.128	1.073	2.923	0.309
Points_last4	0.357	1.429	0.138	0.513	1.671	0.098
Post-Policy	-0.012	0.988	0.140	0.193	1.213	0.219
cum_surprise	0.784	2.190	0.103	-0.034	0.966	0.043
Intercept	1.135	3.110	0.224	0.796	2.217	0.488
Observations		276			120	
C-index		0.838			0.787	

Note: Managerial changes due to nonsport reasons are excluded from the estimation.
Note: The estimation for Liga MX excludes seasons affected by COVID-19.

Table 12: Consequences of within-season managerial dismissals due to sports reasons

	Goal Difference		Victory		Points	
Variable	Coef.	P-val	Coef.	P-val	Coef.	P-val
Intercept	-0.442	0.004	0.275	0.000	1.038	0.000
Home	0.767	0.000	0.168	0.000	0.500	0.000
Average Cumulative Reference Points	0.018	0.727	-0.005	0.723	0.005	0.895
Average Cumulative Opponent Points	-0.283	0.000	-0.075	0.000	-0.203	0.000
Treatment	0.031	0.753	-0.007	0.794	-0.019	0.808
Placebo	0.023	0.784	0.004	0.853	0.024	0.714
Post2020	-0.040	0.591	-0.011	0.625	-0.016	0.787
Treatment:Post2020	-0.293	0.106	-0.010	0.843	-0.131	0.346
Placebo:Post2020	0.199	0.186	0.079	0.069	0.156	0.178
H_0: *Treatment = Placebo (all sample)*	6.744	0.009	3.559	0.059	5.279	0.022
H_0: *Treatment = Placebo (pre policy)*	0.004	0.952	0.094	0.759	0.163	0.687
Adj. R^2	0.110		0.067		0.084	
Observations	3316		3316		3316	

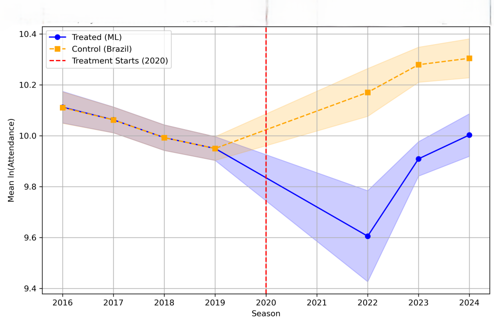
Note: Managerial changes due to nonsport reasons are excluded from the estimation.
Note: COVID years are excluded from the estimation.

Table 13: Consequences of within-season managerial dismissals due to sports reasons (K League)

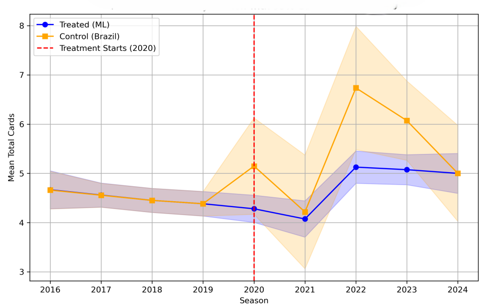
	Goal Difference		Victory		Points	
Variable	Coef.	P-value	Coef.	P-value	Coef.	P-value
Intercept	0.523	0.002	0.506	0.000	1.764	0.000
Home	0.486	0.000	0.115	0.000	0.344	0.000
Average Cumulative Ref. Points	-0.093	0.180	-0.036	0.099	-0.092	0.111
Average Cumulative Opp. Points	-0.488	0.000	-0.120	0.000	-0.353	0.000
Treatment	-0.299	0.024	-0.049	0.232	-0.124	0.255
Placebo	-0.025	0.847	-0.020	0.614	-0.048	0.654
Post2013	-0.228	0.001	-0.080	0.000	-0.179	0.003
Treatment × Post2013	0.182	0.343	-0.001	0.992	-0.065	0.684
Placebo × Post2013	0.023	0.898	0.029	0.601	0.078	0.592
H0: Treatment = Placebo (all sample)	0.453	0.501	1.200	0.273	2.414	0.120
H0: Treatment = Placebo (pre policy)	2.821	0.093	0.324	0.569	0.321	0.571
Adjusted R^2	0.136		0.089		0.108	
Observations	2796		2796		2796	

Note: Managerial changes due to nonsport reasons are excluded from the estimation.

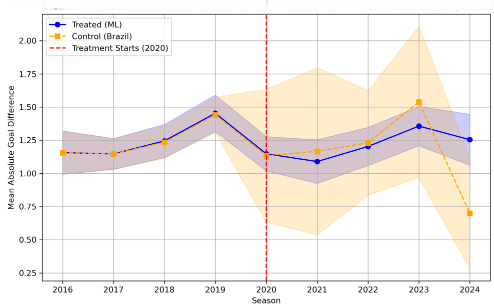
Figures



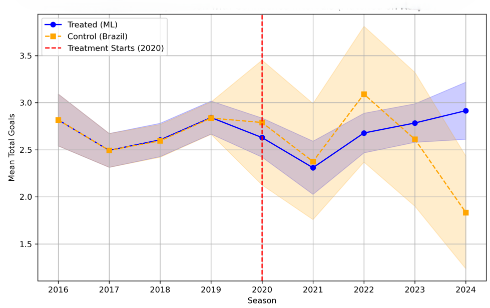
(a) Mean ln(Attendance) by Season (*Liga MX* vs Brasileirão; excluding 2020–2021)



(b) Mean Total Cards by Season (*Liga MX* vs Brasileirão)

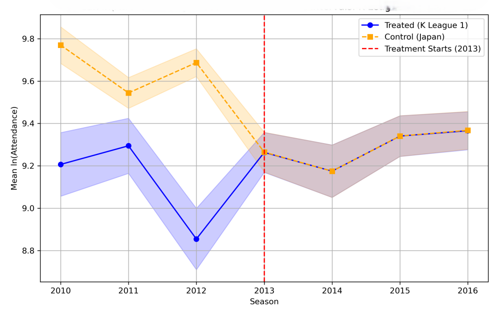


(c) Mean Goal Difference by Season (*Liga MX* vs Brasileirão)

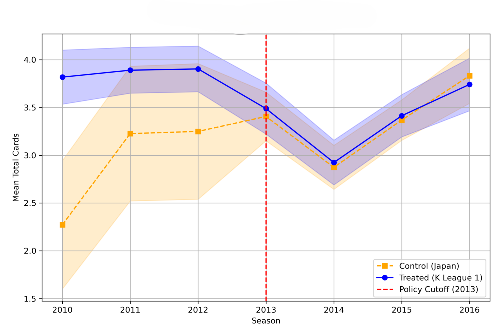


(d) Mean Total Goals by Season (*Liga MX* vs Brasileirão)

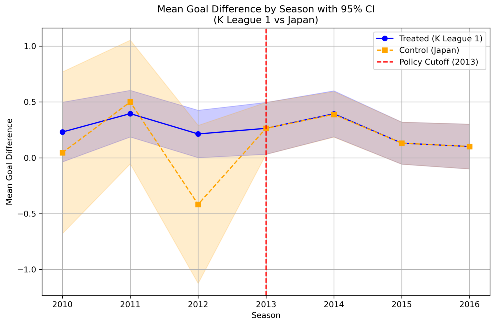
Figure 1: Seasonal averages with 95% confidence intervals. Treated (*Liga MX*) and control (Brasileirão) groups are shown by season.



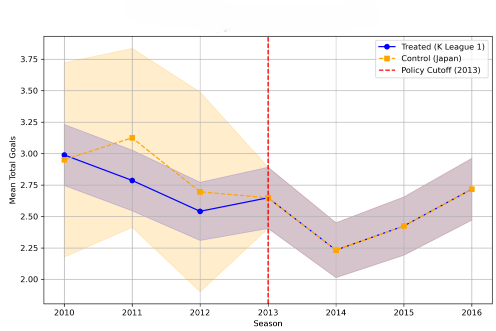
(a) Mean ln(Attendance) by Season (K League 1 vs J1 League)



(b) Mean Total Cards by Season (K League 1 vs J1 League)



(c) Mean Goal Difference by Season (K League 1 vs J1 League)



(d) Mean Total Goals by Season (K League 1 vs J1 League)

Figure 2: Seasonal averages with 95% confidence intervals. Treated (*K-League 1*) and control (J1 League) groups are shown by season.

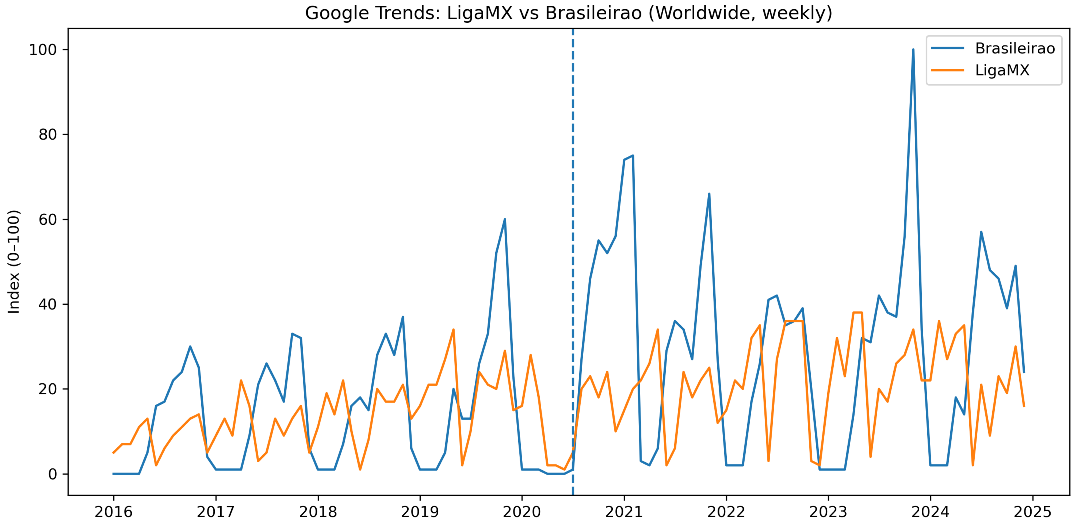


Figure 3: Google Trends comparison of *Liga MX* and the Brasileirão (worldwide, weekly), with the dashed line marking the 2020 introduction of the closed-league format in Mexico.

A Proofs

Standing notation

Let $E \equiv \sum_{j=1}^{n} e_j$ denote total effort. Throughout, F_r is differentiable with $\frac{\partial F_r}{\partial e_i} < 0$ and $\frac{\partial F_r}{\partial e_j} > 0$ for $j \neq i$, and Assumption 1 in the main text holds (interior equilibrium, single-crossing of marginal benefits).

Proof of Lemma 2 (Interior equilibrium characterisation)

Team i's payoff is

$$U_i(e_i; e_{-i}) \;=\; D\,[1 - F_r(e_i; \vec{e})]\,R \;+\; \frac{e_i}{E}V \;-\; c_i e_i^2.$$

For an interior optimum,

$$\frac{\partial U_i}{\partial e_i} = D\Big(-\frac{\partial F_r}{\partial e_i}\Big)R \;+\; V\,\frac{\partial}{\partial e_i}\Big(\frac{e_i}{E}\Big) \;-\; 2c_i e_i = 0.$$

Since $\frac{\partial}{\partial e_i}(e_i/E) = (E - e_i)/E^2 = \big(\sum_{j\neq i} e_j\big)/E^2$, the first-order condition rearranges to

$$2c_i e_i \;=\; \frac{V\sum_{j\neq i} e_j}{E^2} \;+\; D\Big(-\frac{\partial F_r}{\partial e_i}\Big)R.$$

Under the single-crossing condition (marginal benefit decreasing in e_i), the best response is unique and strictly decreasing in c_i, so in any interior equilibrium $c_i < c_k \Rightarrow e_i^* > e_k^*$. ■

Proof sketch of Remark 3 (Comparative statics in r)

From Lemma 2, the first-order condition can be written as

$$2c_i e_i \;=\; \frac{V\sum_{j\neq i} e_j}{E^2} \;+\; \Big(-\frac{\partial F_r}{\partial e_i}\Big)DR.$$

The right-hand side is the sum of a *win component*, $\frac{V\sum_{j\neq i} e_j}{E^2}$, reflecting the marginal benefit of effort for winning the prize V, and a *survival component*, $\big(-\frac{\partial F_r}{\partial e_i}\big)DR$, reflecting the marginal effect of effort on survival when relegation is in place ($D = 1$).

Treating r as a parameter that shifts the location and steepness of the survival boundary, the implicit-function theorem yields

$$\frac{\partial e_i^*}{\partial r} = \frac{DR\,\frac{\partial^2 F_r}{\partial r\,\partial e_i}}{2c_i - \frac{\partial}{\partial e_i}\Big[\frac{V\sum_{j\neq i} e_j}{E^2} + D\Big(-\frac{\partial F_r}{\partial e_i}\Big)\,R\Big]}.$$

For teams near the relegation cut-off, standard regularity implies $\frac{\partial^2 F_r}{\partial r\,\partial e_i} < 0$, and the denominator is positive by single-crossing, giving $\partial e_i^*/\partial r > 0$. The effect is strongest for high-c_i teams (closer to the cut-off). ■

Proof of Proposition 4 (Effect of relegation on effort)

Fix $r \in (0,1)$ and parameters $(V, R, \{c_i\})$. Let $b_i^D(e_{-i})$ denote team i's interior best response under $D \in \{0,1\}$. By Lemma 2,

$$2c_i\, b_i^D(e_{-i}) \;=\; \frac{V\sum_{j\neq i} e_j}{\left(\sum_j e_j\right)^2} \;+\; D\Big(-\frac{\partial F_r}{\partial e_i}\big(b_i^D(e_{-i});\, e_{-i}\big)\Big)R.$$

Holding e_{-i} fixed, the right-hand side is (strictly) larger when $D=1$ than when $D=0$ (because $-\partial F_r/\partial e_i > 0$), while the left-hand side is increasing in b_i^D. Hence

$$b_i^1(e_{-i}) \;\geq\; b_i^0(e_{-i}) \quad \text{for all } e_{-i},$$

with strict inequality whenever the survival term is locally responsive at $b_i^0(e_{-i})$.

Let $e^*(D)$ be the (interior) Nash equilibrium under D. Under Assumption 1, best responses are single-valued and continuous, and the equilibrium is unique. Evaluating at $e^*(0)$ gives

$$b_i^1\big(e_{-i}^*(0)\big) \;\geq\; b_i^0\big(e_{-i}^*(0)\big) \;=\; e_i^*(0),$$

so each player's desired adjustment from $e^*(0)$ is weakly upward when D switches to 1. By standard equilibrium-comparative-statics arguments for concave n-player games (Rosen (1965)), the unique fixed point then satisfies

$$e_i^*(1) \;\geq\; e_i^*(0) \quad \text{for all } i,$$

with strict inequality for any i such that $-\frac{\partial F_r}{\partial e_i}\big(e^*(0)\big)R > 0$. ■

Proof of Corollary 5 (Effect on competitive balance)

Let $e^{(0)} = (e_1^*(0), \ldots, e_n^*(0))$ and $e^{(1)} = (e_1^*(1), \ldots, e_n^*(1))$, and define $\Delta e_i \equiv e_i^*(1) - e_i^*(0)$. Assume w.l.o.g. $e_1^*(0) \geq \cdots \geq e_n^*(0)$ (equivalently $c_1 < \cdots < c_n$), and suppose that for all $i < k$,

$$0 \;\leq\; \Delta e_k - \Delta e_i \;\leq\; e_i^*(0) - e_k^*(0),$$

with at least one strict inequality. Consider any pair (i,k) with $i<k$:

$$\big(e_i^*(1) - e_k^*(1)\big)^2 = \Big[\big(e_i^*(0) - e_k^*(0)\big) - \big(\Delta e_k - \Delta e_i\big)\Big]^2 \;\leq\; \big(e_i^*(0) - e_k^*(0)\big)^2,$$

with strict inequality for at least one pair by assumption. Using the identity

$$\sum_{i=1}^{n}\big(x_i - \bar{x}\big)^2 \;=\; \frac{1}{n}\sum_{i<k}\big(x_i - x_k\big)^2,$$

we conclude that $\mathrm{Var}(e^{(1)}) < \mathrm{Var}(e^{(0)})$. ■

Proof of Theorem 6 (Regulator's implementation of relegation)

By Proposition 4, $\sum_i e_i^*(1) \geq \sum_i e_i^*(0)$, with strict inequality if at least one team has a locally responsive survival term at $e^*(0)$. By Corollary 5, $\mathrm{Var}(e^{(1)}) \leq \mathrm{Var}(e^{(0)})$, with strict inequality under the compression condition. Hence,

$$W(1) - W(0) = \Big[\sum_i e_i^*(1) - \sum_i e_i^*(0)\Big] \;-\; \lambda\Big[\mathrm{Var}(e^{(1)}) - \mathrm{Var}(e^{(0)})\Big] \;>\; 0$$

whenever either (i) total effort rises strictly with $\lambda \geq 0$ and variance does not increase, or (ii) variance falls strictly with $\lambda > 0$. Therefore the regulator chooses $D = 1$. ■

Tables

Table A1: Difference-in-Differences Estimation Results (Log Attendance): *K-League 1* vs J1 League

	All Observations		Low PPG Subsample	
	Coef.	P-value	Coef.	P-value
Panel A: Covariates				
ppg[(1)]	0.134	0.013	-0.254	0.274
ppg_away[(1)]	0.091	0.115	0.073	0.801
size[(2)]	-0.011	0.687	0.199	0.102
size_away[(2)]	-0.049	0.066	-0.091	0.547
probit_diff[(3)]	-0.007	0.966	-0.362	0.285
probit_diff_squared[(3)]	-0.207	0.557	2.985	0.001
post_treatment	0.134	0.001	0.062	0.339
diff_in_diff	-0.195	0.003	-0.211	0.226
Panel B: No Covariates				
post_treatment	0.142	0.001	0.043	0.513
diff_in_diff	-0.157	0.017	-0.204	0.193
AIC	1514.26		115.34	
AIC (no covariates)	1519.68		144.28	
Observations	1603		499	
F-statistic	3.53	0.001	2.24	0.025
Pre-trend F-test	0.00007	0.993	5.77	0.017

Note: All regressions include fixed effects for fixtures and use standard errors clustered at the fixture level. Estimates correspond to OLS models.

(1) *ppg* refers to points per match.
(2) *size* is a performance-based measure calculated as a weighted average of a team's points per match over the five most recent seasons, giving more weight to recent performance (weights $= 1, 1/2, \ldots, 1/5$).
(3) *probit_ diff* is the difference in the ex-ante probability to win the match. Probabilities are obtained from the betting market or, when unavailable, estimated using an ordered probit model.

Table A2: Difference-in-Differences Estimation (Log Attendance): *K-League 1* vs J1 League
[Excludes Teams Involved in Corruption Episodes]

	All Matched Observations	
	Coef.	P-value
Panel A: Covariates		
ppg$^{(1)}$	0.091	0.131
ppg_away$^{(1)}$	0.163	0.015
size$^{(2)}$	-0.026	0.333
size_away$^{(2)}$	-0.030	0.292
prob_diff$^{(3)}$	-0.084	0.614
prob_diff_squared$^{(3)}$	-0.059	0.895
post_treatment	0.133	0.001
diff_in_diff	-0.422	0.003
Panel B: No Covariates		
post_treatment	0.142	0.001
diff_in_diff	-0.379	0.007
AIC	143.21	
Observations	827	
F-statistic	7.47	0.00072
Pre-trend F-test	13.18	0.00035

Note: All regressions include fixed effects for fixtures and use standard errors clustered at the fixture level. Estimates correspond to OLS models. The estimation sample excludes all matches involving teams implicated in corruption episodes affecting the 2011 season.

(1) *ppg* refers to points per match.
(2) *size* is a performance-based measure calculated as a weighted average of a team's points per match over the five most recent seasons, giving more weight to recent performance (weights $= 1, 1/2, \ldots, 1/5$).
(3) *prob_ diff* is the difference in the ex-ante probability to win the match. Probabilities are obtained from the betting market or, when unavailable, estimated using an ordered probit model.

Additional note: The Low PPG subsample is not reported because the DiD interaction is not identified in that restricted sample; treated fixtures do not display sufficient variation across pre- and post-2013 periods.

Table A3: Difference-in-Differences Estimation (Log Attendance): *K-League 1* vs J1 League
[Excludes 2012 Season]

	All Observations		Low PPG Subsample	
	Coef.	P-value	Coef.	P-value
Panel A: Covariates				
ppg$^{(1)}$	0.187	0.002	-0.081	0.718
ppg_away$^{(1)}$	0.092	0.146	-0.117	0.691
size$^{(2)}$	0.022	0.447	0.200	0.125
size_away$^{(2)}$	-0.029	0.348	0.020	0.904
prob_diff$^{(3)}$	-0.244	0.202	-0.153	0.682
prob_diff_squared$^{(3)}$	0.083	0.821	1.757	0.026
post_treatment	0.118	0.003	0.071	0.303
diff_in_diff	-0.058	0.401	0.002	0.994
Panel B: No Covariates				
post_treatment	0.129	0.001	0.060	0.383
diff_in_diff	-0.032	0.639	-0.006	0.974
AIC	914.12		-132.29	
AIC (no covariates)	925.47		-114.78	
Observations	1330		436	
F-statistic	3.876	0.0002	1.789	0.080
Pre-trend F-test	0.006	0.940	71.445	0.000

Note: All regressions include fixed effects for fixtures and use standard errors clustered at the fixture level. The dependent variable is the natural logarithm of match attendance. Estimates correspond to OLS models. This robustness check excludes the 2012 season.

(1) *ppg* refers to points per match.
(2) *size* is a performance-based measure calculated as a weighted average of a team's points per match over the five most recent seasons, giving more weight to recent performance (weights $= 1, 1/2, \ldots, 1/5$).
(3) *prob_ diff* is the difference in the ex-ante probability to win the match. Probabilities are obtained from the betting market or, when unavailable, estimated using an ordered probit model.

Table A4: Difference-in-Differences Estimation Results (Total Cards): *K-League 1* vs J1 League (Excluding 2012)

	All Observations		Low PPG Subsample	
	Coef.	P-value	Coef.	P-value
Panel A: Covariates				
home_history$^{(1)}$	-0.008	0.483	-0.084	0.000
away_history$^{(1)}$	0.024	0.036	0.079	0.000
ppg$^{(2)}$	-0.080	0.567	0.118	0.648
ppg_away$^{(2)}$	-0.090	0.519	-0.889	0.006
size$^{(3)}$	0.019	0.891	0.050	0.850
size_away$^{(3)}$	0.009	0.952	0.520	0.029
post_treatment	-0.890	0.134	0.190	0.520
diff_in_diff	1.988	0.000	0.193	0.514
Panel B: No Covariates				
post_treatment	-1.457	0.002	-5.000	0.000
diff_in_diff	1.896	0.000	5.346	0.000
AIC	4715.47		1340.64	
AIC (no covariates)	6589.62		1707.61	
Observations	1277		414	
F-statistic	3.783	0.000	9154.694	0.000
Pre-trend F-test	0.247	0.620	0.010	0.921

Note: All regressions include fixed effects for fixtures and use standard errors clustered at the fixture level. The dependent variable is the total number of cards per match, counting a red card as two yellows. Estimates correspond to OLS models. This robustness check excludes the 2012 season.

(1) *home_history* and *away_history* are the number of months between each club's foundation date and the match date (home and away, respectively).
(2) *ppg* and *ppg_away* are the average points per game of the home and away teams at the time of the match.
(3) *size* is a performance-based measure computed as a weighted average of points per game over the previous five seasons (weights 1, 1/2, . . . , 1/5).

The pre-trend F-test is computed over the post-2013 seasons, consistent with the reverse DiD setup.

Table A5: Difference-in-Differences Estimation Results (Absolute Goal Difference): Korea vs Japan (Excluding 2012)

	All Observations		Low PPG Subsample	
	Coef.	P-value	Coef.	P-value
Panel A: With Covariates				
diff_points$^{(1)}$	0.021	0.691	0.110	0.239
diff_size$^{(2)}$	0.143	0.016	0.045	0.629
post_treatment	-0.867	0.003	-0.049	0.916
diff_in_diff	0.974	0.001	-0.025	0.959
Panel B: No Covariates				
post_treatment	-0.873	0.002	-0.022	0.962
diff_in_diff	0.980	0.001	0.004	0.994
AIC	3205.91		850.87	
AIC (no covariates)	4412.54		1232.12	
Observations	1240		420	
F-statistic	3.965	0.004	0.538	0.708
Pre-trend F-test	0.000	0.993	0.672	0.414

Note: The dependent variable is the absolute goal difference per match. All regressions include fixture fixed effects, with standard errors clustered at the fixture level.

(1) *diff_points* is the difference in average points per game (PPG) at baseline.
(2) *diff_size* is the difference in average performance (PPG) over the previous five seasons.

Table A6: Difference-in-Differences Estimation Results (Total Goals): *K-League 1* vs Japan (Excluding 2012)

	All Observations		Low PPG Subsample	
	Coef.	P-value	Coef.	P-value
Panel A: Covariates				
history	0.023	0.130	0.004	0.480
history_away	-0.027	0.097	0.004	0.480
ppg	-0.040	0.750	0.257	0.293
ppg_away	-0.009	0.943	-0.160	0.477
size	0.284	0.119	-0.044	0.874
size_away	-0.106	0.561	0.229	0.344
post_treatment	-0.456	0.432	-0.122	0.909
diff_in_diff	0.710	0.176	0.637	0.349
Panel B: No Covariates				
post_treatment	-0.128	0.784	-1.000	0.000
diff_in_diff	0.506	0.293	1.202	0.000
AIC	4693.04		1449.77	
AIC (no covariates)	6385.45		1677.19	
Observations	1325		478	
F-statistic	1.749	0.086	1.773	0.106
Pre-trend F-test	0.000	1.000	5.105	0.025

Note: All regressions include fixed effects for fixtures and use standard errors clustered at the fixture level. The dependent variable is the total number of goals per match.

Table A7: Difference-in-Differences Estimation Results (*Liga MX* vs Brazil)

	Log Attendance		Total Cards		Absolute Goal Difference		Total Goals	
	Coef.	P-value	Coef.	P-value	Coef.	P-value	Coef.	P-value
post_treatment	0.174	0.035	0.781	0.575	-0.734	0.466	-1.278	0.057
diff_in_diff	-0.495	0.000	-0.744	0.598	0.362	0.722	0.902	0.184
Linear trend Brazil	0.037	0.351	-0.173	0.826	0.496	0.359	0.490	0.163
Linear trend Mexico	-0.152	0.000	-0.248	0.009	-0.017	0.820	0.121	0.010
Quadratic trend Brazil	-0.001	0.709	0.011	0.873	-0.062	0.163	-0.058	0.062
Quadratic trend Mexico	0.021	0.000	0.038	0.001	0.016	0.064	-0.004	0.474
GDP growth Brazil	-0.026	0.166	-0.085	0.577	-0.013	0.861	0.089	0.210
GDP growth Mexico	-0.036	0.000	0.022	0.204	-0.029	0.014	-0.010	0.188
AIC	3181.090		12765.762		10203.259		7546.583	
F-statistic	19.768	0.000	3.939	0.000	2.844	0.004	4.449	0.000
Observations	3215		3171		3129		3110	

Note: All regressions include fixture fixed effects, with standard errors clustered at the fixture level. P-values are rounded to three decimals; 0.000 denotes $p < 0.001$.

Table A8: Difference-in-Differences Estimation Results

	Log Attendance		Total Cards		Absolute Goal Difference		Total Goals	
	Coef.	P-value	Coef.	P-value	Coef.	P-value	Coef.	P-value
post_treatment	0.251	0.003	-0.432	0.527	-0.841	0.038	-1.005	0.376
diff_in_diff	-1.387	0.000	0.185	0.823	1.118	0.284	0.059	0.961
Linear trend Japan	0.038	0.045	0.190	0.321	-0.066	0.182	-0.216	0.446
Linear trend Korea	-0.409	0.000	-0.285	0.100	0.091	0.787	-0.424	0.012
Quadratic trend Japan	0.007	0.172	-0.007	0.907	-0.054	0.404	-0.081	0.608
Quadratic trend Korea	0.111	0.000	0.128	0.010	-0.028	0.417	0.144	0.003
GDP growth Japan	0.029	0.022	-0.298	0.110	0.065	0.346	0.115	0.687
GDP growth Korea	-0.318	0.000	-0.379	0.024	0.132	0.696	-0.339	0.037
AIC	1424.276		7633.235		5288.397		7464.293	
F-statistic	7.909	0.000	5.920	0.000	1.758	0.085	3.048	0.003
Observations	1603		2242		2244		2241	

Note: All regressions include fixture fixed effects, with standard errors clustered at the fixture level. P-values are rounded to three decimals; 0.000 denotes $p < 0.001$.

Table A9: Difference-in-Differences Estimation Results (Absolute Goal Difference): *Liga MX* vs Brazil (Excluding 2024)

	All Observations		Low PPG Subsample	
	Coef.	P-value	Coef.	P-value
Panel A: Covariates				
diff_points	0.009	0.813	0.047	0.477
diff_size	-0.005	0.927	0.058	0.525
var	0.254	0.002	0.134	0.344
post_treatment	-1.007	0.007	-0.969	0.087
diff_in_diff	0.903	0.016	0.904	0.111
Panel B: No Covariates				
post_treatment	-0.786	0.030	-0.857	0.079
diff_in_diff	0.791	0.031	0.854	0.089
AIC	4709.57		1372.00	
AIC (no covariates)	7247.99		2063.92	
Observations	1688		596	
F-statistic	3.340	0.006	0.839	0.523
Pre-trend F-test	0.001	0.977	62.505	0.000

Note: The dependent variable is the absolute goal difference per match. All regressions include fixed effects for fixtures and use standard errors clustered at the fixture level. The sample excludes season 2024. P-values are rounded to three decimals; 0.000 denotes $p < 0.001$.

Table A10: Difference-in-Differences Estimation Results (Total Goals): *Liga MX* vs Brazil (Excluding 2024)

	All Observations		Low PPG Subsample	
	Coef.	P-value	Coef.	P-value
Panel A: Covariates				
home_history	-4.292e+11	1.000	0.003	0.381
away_history	4.292e+11	0.240	0.003	0.381
avg_cum_home_points	0.076	1.000	0.327	0.049
avg_cum_away_points	-0.032	0.704	-0.003	0.988
size	0.098	0.327	0.188	0.382
size_away	-0.077	0.457	-0.094	0.599
var	0.108	0.412	-0.226	0.386
post_treatment	-0.864	1.000	-1.390	0.111
diff_in_diff	0.635	0.169	1.364	0.111
Panel B: No Covariates				
post_treatment	-0.548	0.250	-1.105	0.196
diff_in_diff	0.583	0.228	1.227	0.158
AIC	6614.90		2426.47	
AIC (no covariates)	9709.98		3532.99	
Observations	1903		786	
F-statistic	0.000	1.000	1.075	0.381
Pre-trend F-test	0.000	0.986	0.014	0.905

Note: Dependent variable is the total number of goals per match. All regressions include fixed effects for fixtures and use standard errors clustered at the fixture level. Sample excludes season 2024. P-values are rounded to three decimals; 0.000 denotes $p < 0.001$.

Table A11: Within-Season Managerial Changes in Liga MX, 2016–2024

Season	Round	Team	Old Manager	New Manager	Reason
Apertura 2016/2017	6	Santos Laguna	Luis Zubeldía	José De La Torre	Sports results
Apertura 2016/2017	8	Club León	Luis Tena	Javier Torrente	Sports results
Apertura 2016/2017	9	Chiapas FC	José Cardozo	Sergio Bueno	Sports results
Apertura 2016/2017	11	CD Veracruz	Pablo Marini	Carlos Reinoso	Own resignation (poor performance)
Apertura 2016/2017	11	CF América	Ignacio Ambriz	Ricardo La Volpe	Sports results
Apertura 2016/2017	14	Cruz Azul	Tomás Boy	Joaquín Moreno	Own resignation (poor performance)
Apertura 2017/2018	7	Club León	Javier Torrente	Rubén Ayala	Sports results
Apertura 2017/2018	7	Pumas UNAM	Francisco Palencia	Sergio Egea	Sports results
Apertura 2017/2018	8	Club León	Rubén Ayala	Gustavo Díaz	Conclusion caretaker role
Apertura 2017/2018	11	CD Veracruz	Juan Antonio Luna	José Cardozo	Sports results
Apertura 2017/2018	11	Puebla FC	Jose García	Ignacio Sánchez	Sports results
Apertura 2017/2018	12	Santos Laguna	José De La Torre	Robert Siboldi	Sports results

Table A11 – continued from previous page

Season	Round	Team	Old Manager	New Manager	Reason
Apertura 2017/2018	13	Puebla FC	Ignacio Sánchez	Enrique Meza	Sports results
Apertura 2017/2018	13	Pumas UNAM	Sergio Egea	David Patiño	Own resignation (poor performance)
Apertura 2018/2019	4	Santos Laguna	Robert Siboldi	Salvador Reyes	Breach of internal ethics
Apertura 2018/2019	5	CD Veracruz	Guillermo Vázquez	Hugo Chávez	Dispute over "double contracts"
Apertura 2018/2019	8	CD Veracruz	Hugo Chávez	Juvenal Olmos	Conclusion caretaker role
Apertura 2018/2019	9	Atlas Guadalajara	Gerardo Espinoza	Guillermo Hoyos	Sports results
Apertura 2018/2019	10	Club León	Gustavo Díaz	Ignacio Ambriz	Sports results
Apertura 2018/2019	14	Club Necaxa	Marcelo Leaño	Jorge Martínez	Sports results
Apertura 2018/2019	15	CD Veracruz	Juvenal Olmos	Hugo Chávez	Sports results
Apertura 2019/2020	6	Monarcas Morelia	Javier Torrente	Pablo Guede	Sports results
Apertura 2019/2020	6	Puebla FC	José Sánchez	Octavio Becerril	Sports results
Apertura 2019/2020	7	Puebla FC	Octavio Becerril	Juan Reynoso	Conclusion caretaker role
Apertura 2019/2020	8	CD Veracruz	Enrique Meza	José González China	Own resignation (poor performance)

Table A11 – continued from previous page

Season	Round	Team	Old Manager	New Manager	Reason
Apertura 2019/2020	9	Atlético San Luis	Luis Sosa	Gustavo Matosas	Disrespectful comments about players and the president
Apertura 2019/2020	9	CD Veracruz	José González China	Enrique López	Conclusion caretaker role
Apertura 2019/2020	9	Cruz Azul	Pedro Caixinha	Robert Siboldi	Sports results
Apertura 2019/2020	12	Deportivo Guadalajara	Tomás Boy	Luis Tena	Sports results
Apertura 2019/2020	13	CF Monterrey	Diego Alonso	José Treviño	Sports results
Apertura 2019/2020	16	Atlético San Luis	Gustavo Matosas	Luis García	Sports results
Apertura 2019/2020	17	CF Monterrey	José Treviño	Antonio Mohamed	Conclusion caretaker role
Apertura 2019/2020	19	Deportivo Toluca	Ricardo La Volpe	José De La Torre	Sports results
Apertura 2020/2021	4	Deportivo Guadalajara	Luis Tena	Marcelo Leaño	Sports results
Apertura 2020/2021	4	Atlas Guadalajara	Rafael Puente	Rubén Duarte	Sports results
Apertura 2020/2021	5	Deportivo Guadalajara	Marcelo Leaño	Víctor Vucetich	Conclusion caretaker role
Apertura 2020/2021	6	Atlas Guadalajara	Rubén Duarte	Diego Cocca	Conclusion caretaker role
Apertura 2020/2021	8	Club Necaxa	Luis Sosa	José Guadalupe Cruz	Sports results

Table A11 – continued from previous page

Season	Round	Team	Old Manager	New Manager	Reason
Apertura 2020/2021	13	Deportivo Toluca	José De La Torre	Alejandro Domínguez	Sports results
Apertura 2020/2021	14	Mazatlán FC	Francisco Palencia	Tomás Boy	Sports results
Apertura 2020/2021	16	Gallos Blancos	Alex Diego	Héctor Altamirano	Sports results
Apertura 2020/2021	17	Atlético San Luis	Guillermo Vázquez	Unknown	Sports results
Apertura 2022/2023	11	Cruz Azul	Diego Aguirre	Raúl Gutiérrez	Sports results
Apertura 2023/2024	4	Cruz Azul	Ricardo Ferretti	Joaquín Moreno	Sports results
Apertura 2023/2024	6	Puebla FC	Eduardo Arce	Ricardo Carbajal	Sports results
Apertura 2023/2024	7	Club Necaxa	Rafael Dudamel	Luis Padilla	Sports results
Apertura 2023/2024	8	Club Necaxa	Luis Padilla	Eduardo Fentanes	Conclusion caretaker role
Apertura 2023/2024	14	Deportivo Toluca	Ignacio Ambriz	Carlos Morales	Sports results
Apertura 2023/2024	15	Atlas Guadalajara	Benjamín Mora	Omar Flores	Sports results
Clausura 2016/2017	5	Gallos Blancos	Víctor Vucetich	Jaime Lozano	Sports results
Clausura 2016/2017	5	Puebla FC	Ricardo Valiño	José Cardozo	Sports results
Clausura 2016/2017	6	Monarcas Morelia	Pablo Marini	Roberto Hernández	Sports results

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Season	Round	Team	Old Manager	New Manager	Reason
Clausura 2016/2017	12	CD Veracruz	Carlos Reinoso	Juan Antonio Luna	Health problems
Clausura 2017/2018	3	Atlas Guadalajara	José Guadalupe Cruz	Rubén Romano	Sports results
Clausura 2017/2018	13	Atlas Guadalajara	Rubén Romano	Gerardo Espinoza	Sports results
Clausura 2017/2018	14	Lobos BUAP	Rafael Puente	Daniel Alcántar	Sports results
Clausura 2018/2019	4	CF Pachuca	Pako Ayestárán	Martín Palermo	Sports results
Clausura 2018/2019	5	Pumas UNAM	David Patiño	Bruno Marioni	Sports results
Clausura 2018/2019	7	Puebla FC	Enrique Meza	José Sánchez	Sports results
Clausura 2018/2019	8	Gallos Blancos	Rafael Puente	Víctor Vucetich	Sports results
Clausura 2018/2019	9	Monarcas Morelia	Roberto Hernández	Javier Torrente	Sports results
Clausura 2018/2019	9	Deportivo Toluca	Rolando Hernán Cristante	José Real	Sports results
Clausura 2018/2019	10	Deportivo Toluca	José Real	Ricardo La Volpe	Conclusion caretaker role
Clausura 2018/2019	11	Atlas Guadalajara	Guillermo Hoyos	Leandro Cufré	Sports results
Clausura 2018/2019	13	Deportivo Guadalajara	José Cardozo	Alberto Coyote	Sports results
Clausura 2018/2019	13	Santos Laguna	Salvador Reyes	Rubén Duarte	Sports results

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Season	Round	Team	Old Manager	New Manager	Reason
Clausura 2018/2019	14	Deportivo Guadalajara	Alberto Coyote	Tomás Boy	Conclusion caretaker role
Clausura 2018/2019	15	CD Veracruz	Robert Siboldi	José González China	Own resignation (poor performance)
Clausura 2018/2019	15	Santos Laguna	Rubén Duarte	Jorge Guillermo Almada	Sports results
Clausura 2019/2020	4	Atlas Guadalajara	Leandro Cufré	Omar Flores	Sports results
Clausura 2019/2020	5	Atlas Guadalajara	Omar Flores	Rafael Puente	Sports results
Clausura 2020/2021	12	Club Necaxa	José Guadalupe Cruz	Guillermo Vázquez	Sports results
Clausura 2020/2021	12	FC Juárez	Luis Tena	Luis Sosa	Sports results
Clausura 2020/2021	15	Club Tijuana	Pablo Guede	Ildefonso Mendoza	Sports results
Clausura 2020/2021	16	Club Tijuana	Ildefonso Mendoza	Robert Siboldi	Sports results
Clausura 2021/2022	4	Atlético San Luis	Marcelo Méndez	André Jardine	Sports results
Clausura 2021/2022	5	Club Necaxa	Pablo Guede	Jaime Lozano	Sports results
Clausura 2021/2022	5	Gallos Blancos	Leo Ramos	Rolando Hernán Cristante	Sports results
Clausura 2021/2022	7	Santos Laguna	Pedro Caixinha	Eduardo Fentanes	Sports results
Clausura 2021/2022	8	CF Monterrey	Javier Aguirre	Hugo Castillo	Sports results

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Season	Round	Team	Old Manager	New Manager	Reason
Clausura 2021/2022	9	CF América	Santiago Solari	Fernando Ortiz	Sports results
Clausura 2021/2022	9	CF Monterrey	Hugo Castillo	Víctor Vucetich	Conclusion caretaker role
Clausura 2021/2022	10	Mazatlán FC	Beñat San José	Christian Ramírez	Sports results
Clausura 2021/2022	11	Mazatlán FC	Christian Ramírez	Gabriel Caballero	Sports results
Clausura 2021/2022	15	Deportivo Guadalajara	Marcelo Leaño	Ricardo Cadena	Sports results
Clausura 2021/2022	16	Club León	Ariel Holan	Christian Martínez	Sports results
Clausura 2022/2023	5	Mazatlán FC	Gabriel Caballero	Christian Ramírez	Sports results
Clausura 2022/2023	6	Club Tijuana	Ricardo Valiño	Miguel Herrera	Sports results
Clausura 2022/2023	6	Mazatlán FC	Christian Ramírez	Rubén Romano	Conclusion caretaker role
Clausura 2022/2023	6	UANL Tigres	Diego Cocca	Marco Ruiz	Own resignation (poor performance)
Clausura 2022/2023	8	Cruz Azul	Raúl Gutiérrez	Joaquín Moreno	Sports results
Clausura 2022/2023	7	Cruz Azul	Joaquín Moreno	Ricardo Ferretti	Conclusion caretaker role
Clausura 2022/2023	13	Pumas UNAM	Rafael Puente	Antonio Mohamed	Sports results
Clausura 2022/2023	14	FC Juárez	Rolando Hernán Cristante	Diego Mejía	Sports results

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Season	Round	Team	Old Manager	New Manager	Reason
Clausura 2022/2023	15	UANL Tigres	Marco Ruiz	Robert Siboldi	Sports results
Clausura 2022/2023	17	Santos Laguna	Eduardo Fentanes	Pablo Repetto	Sports results
Clausura 2023/2024	5	FC Juárez	Diego Mejía	Antonio Torres Servín	Sports results
Clausura 2023/2024	6	FC Juárez	Antonio Torres Servín	Mauricio Nogueira	Conclusion caretaker role
Clausura 2023/2024	7	Santos Laguna	Pablo Repetto	Ignacio Ambriz	Own resignation (poor performance)
Clausura 2023/2024	10	Puebla FC	Ricardo Carbajal	Isaac Moreno	Sports results
Clausura 2023/2024	12	Puebla FC	Isaac Moreno	Andrés Carevic	Sports results
Clausura 2023/2024	15	Mazatlán FC	Ismael Rescalvo	Gilberto Adame	Sports results

Table A12: Within-Season Managerial Changes in K League, 2010–2016

Season	Round	Team	Old Manager	New Manager	Reason
2010	14	Incheon United	Ilija Petković	Bong-gil Kim (caretaker)	Due to his wife's health problems
2010	16	Incheon United	Bong-gil Kim	Jung-Moo Huh	Conclusion caretaker role
2010	13	Pohang Steelers	Waldemar Lemos	Chang-hyeon (caretaker)	Sports results
2010	13	Suwon Bluewings	Beom-geun Cha	Sung-Hyo Yoon	Sports results
2011	16	Daejeon Citizen	Sun-Jae Wang	Sang-chul Yoo	Match fixing scandals
2011	8	FC Seoul	Kwan Hwangbo	Yong-soo Choi	Sports results
2011	4	Gangwon FC	Soon-ho Choi	Sang-Ho Kim	Sports results
2012	8	Incheon United	Jung-Moo Huh	Bong-Gil Kim	Sports results
2012	27	Chunnam Dragons	Hae-Seong Jung	Sang-Rae Roh (caretaker)	After not qualifying for playoffs
2013	14	Gyeongnam FC	Jin-Han Choi	Cha-man Lee	Sports results
2013	14	Jeonbuk FC	Fabio Lefundes	Kang-hee Choi	Conclusion caretaker role
2013	9	Daegu FC	Seongjeung Dang	Deok-ju Choi	Resignation due to sports results
2014	21	Gyeongnam FC	Cha-Man Lee	Branko Babić	Sports results
2014	10	Seongnam FC	Jong-Hwan Park	Sang-Yoon Lee	Serious misconduct scandal
2015	23	Busan IPark	Sung-Hyo Yoon	Denis Iwamura	Sports results
2015	12	Daejeon Citizen	Jin-ho Cho	Young-Min Kim (caretaker)	Sports results
2015	22	Daejeon Citizen	Young-Min Kim	Moon-Sik Choi	Conclusion caretaker role
2016	16	FC Seoul	Yong-soo Choi	Sun-hong Hwang	Voluntary due to a higher-paying offer
2016	29	Incheon United	Do-hoon Kim	Ki-hyung Lee	Sports results

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Season	Round	Team	Old Manager	New Manager	Reason
2016	33	Pohang Steelers	Jin-cheul Choi	Soon-ho Choi	Sports results

Table A13: Determinants of spell durations in the K League. Accelerated Failure Time (AFT) model (Post2012 cutoff)

Covariate	Coef.	Exp(Coef)	SE(Coef)
Experience	-0.027	0.973	0.012
Nationality	1.065	2.900	0.304
Points_last4	0.512	1.668	0.096
Post-2012	0.246	1.279	0.208
cum_surprise	-0.037	0.964	0.042
Intercept	0.701	2.015	0.499
Observations		120	
C-index		0.784	

Note: Managerial changes due to nonsport reasons are excluded from the estimation.
Note: Post-policy is defined as seasons from 2012 onward.

Table A14: Consequences of within-season managerial dismissals due to sports reasons (K League, Post2012)

	Goal Difference		Victory		Points	
Variable	Coef.	P-value	Coef.	P-value	Coef.	P-value
Intercept	0.539	0.002	0.502	0.000	1.762	0.000
Home	0.486	0.000	0.115	0.000	0.343	0.000
Average Cumulative Ref. Points	-0.080	0.248	-0.029	0.178	-0.078	0.171
Average Cumulative Opp. Points	-0.486	0.000	-0.119	0.000	-0.352	0.000
Treatment	-0.413	0.005	-0.076	0.094	-0.205	0.090
Placebo	-0.160	0.360	-0.028	0.606	-0.095	0.511
Post2012	-0.241	0.001	-0.068	0.004	-0.167	0.008
Treatment × Post2012	0.329	0.085	0.043	0.471	0.076	0.632
Placebo × Post2012	0.215	0.284	0.036	0.566	0.130	0.435
H0: Treatment = Placebo (all sample)	0.873	0.350	0.776	0.378	1.754	0.186
H0: Treatment = Placebo (pre policy)	1.527	0.217	0.564	0.453	0.416	0.519
Adjusted R^2	0.135		0.087		0.106	
Observations	2796		2796		2796	

Note: Managerial changes due to nonsport reasons are excluded from the estimation. Post-policy period is defined as 2012 and onward.

Figures

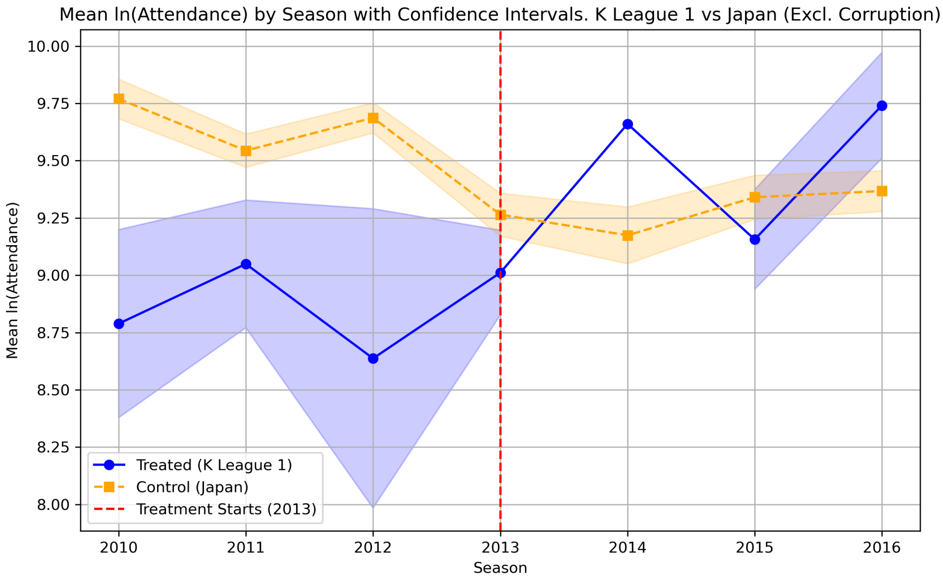

Figure A1: Mean ln(Attendance) by Season with Confidence Intervals. K League 1 vs Japan (Excluding Corruption)