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Moral Support and Performance

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Abstract. This study presents unique empirical evidence on the importance of moral support for performance. We take advantage of an unusual change in Argentinean football legislation. In August 2013, as a matter of national security, the Argentinean government forced all teams in the first division to play their games with only home team supporters. Supporters of visiting teams were not allowed to be in stadiums during league games. We estimate the effect of this exogenous variation of supporters on team performance and find that visiting teams are on average about 20% more likely to lose without the presence of their supporters. As a counterfactual experiment, we run the analysis using contemporaneous cup games, where the visiting team supporters were allowed to attend, and find no effect of the ban on those games. Moreover, the ban does not seem to bias the decisions of referees, the lineups, or the market value of the teams, suggesting that the effect on team performance is due to the loss of moral support rather than other factors. Finally, we find that moral support is more relevant when there is equal power between the two teams, suggesting that moral support compensates the power of monetary resources. This paper provides a proof of concept of moral support as an important nonmonetary resource, even in settings with high monetary incentives.

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1. Introduction

Moral support is defined as giving support to a person or cause without making any contribution beyond the emotional or psychological value of the encouragement. As humans, we spend considerable time supplying and demanding moral support. We use pep talks, encouraging words, and similar unverifiable soft information to boost confidence and "motivate" others. Billions of dollars are spent on books and counseling by people who pay to be inspired and motivated. Encouragement, praise, and motivation strategies are a central theme in management, coaching, education, and political marketing (Kinlaw 1999).

According to Albert Bandura, the way moral support can improve performance is by enhancing self-confidence beliefs (Bandura 1986).[1] As shown by Albrecht et al. (2014), verbal rewards praising one's competence enhance perceived self-determination, increase intrinsic motivation, and activate brain areas associated with subjective valuation of situations, suggesting that people have a higher subjective value for succeeding in a task after verbal reinforcement. In line with this evidence, moral support is formalized in economics as a confidence enhancement strategy in a principal-agent model (Benabou and Tirole 2003). In such a model, the agent has imperfect knowledge about his or her own ability, and the principal, who has stakes in the agent's performance, can send a signal that the agent is of a high ability type to boost agents' self-confidence and consequently improve his or her performance.

Despite its prevalence and importance, the evidence of the effect of moral support on behavior is rather scarce. The major empirical challenge resides in the fact that moral support is essentially endogenous. People choose whether to supply or demand moral support, the extent of it, to whom to supply it, and from whom to demand it. For example, better-performing people (being children, students, workers, or teams) attract higher support (from parents, teachers, bosses, or fans), and at the same time, people who receive more support perform better. This imposes a real challenge for identification of the causal relationship between moral support and human behavior.

This paper addresses this challenge by taking advantage of an exogenous negative shock on moral support caused by an unexpected change of law in the

Argentinean football league. Following an incident in which a football supporter was killed, the authorities decided to implement a drastic measure in the form of a ban forbidding the presence of visiting teams' supporters during first-division games. After the law was implemented, only home team supporters could attend, whereas the visitors' stands remained empty. This provides an unusually clean opportunity in a real-world environment to discern the effect of moral support on behavior.

Using data from 1,320 games played before and after the introduction of the ban, we document a solid negative effect of the ban on the performance of visiting teams. Specifically, the probability that a visiting team loses a game increases by about 20% without their supporters. Moreover, the odds that the visiting team concedes an additional goal more than the home team increases by 1.3 times with the law. These effects are robust for different specifications, sample restrictions, time and season fixed effects, and different time trends. As a robustness check, we run a counterfactual test using data from contemporaneous cup games, where the visitors' supporters were allowed to attend. We find no effect of the ban on these games, which provides additional empirical support for our main finding.

Once we establish the effect of the ban on visiting team performance, we provide evidence suggesting that the ban does not affect performance other than through its effect on moral support. First, we find that the ban does not seem to increase referee hostility toward visiting teams. After the law, referees are neither more likely to give red or yellow cards to visiting players nor more likely to inflict more penalties against visiting teams. Second, we show that the ban does not affect the players' market value. Third, we provide evidence that managers do not respond strategically to the ban and do not change the lineup of their teams for home versus away games. Finally, we show that lack of moral support affects smaller teams more, and it affects bigger teams only when they play against other big teams. This suggests that moral support compensates for the power of monetary resources.

Previous research has shown that providing children with moral and emotional support like verbal praising, company, and attention from teachers, mentors, or parents improves school performance (Darolia and Wydick 2011, Behncke 2012) and pro-sociality (Kosse et al. 2019) and reduces depression and chronic mental health conditions in adulthood (Shaw et al. 2004). Moreover, it has been shown that the risk of academic failure among children can be moderated by support from teachers (Hamre and Pianta 2005) and parental involvement (Auerbach 2009). Another set of studies evaluates the impact of support through mentoring programs on graduate students. In an important contribution, Oreopoulos and Petronijevic (2018) found that a one-to-one coaching program providing regular support to university students has large effects on academic performance. A challenge that this literature faces is to isolate pure *moral* support that parents, mentors, and teachers provide from the *practical* support they give in the form of information and knowledge.

To the best of our knowledge, this is the first paper providing well-identified field evidence on moral support and its causal effect on performance in a highly competitive and professional environment. The most related strand of the literature analyzes the effect of support on children and students' behavior (Albrecht et al. 2014). We complement this literature in two important ways. First, we leverage a natural setting in which the aspect of practical support is not present. In this way, we can study the effect of moral support in isolation. Second, in the literature of education, monetary incentives to students are not typically present. We add to this literature by showing the effect of moral support in a setting where monetary incentives exist and are high.

More generally, this paper adds to the behavioral economics literature highlighting the effectiveness of various forms of nonmonetary incentives on motivation and performance (Deci 1971, Frey and Jegen 2001, Gneezy et al. 2011). For instance, Deci (1971) showed that providing praise increases students' willingness to work on a puzzle. More recently, in a controlled field experiment with students, Bradler et al. (2016) found that unexpected public recognition by means of a thank-you card increases students' group performance. Davies and Fafchamps (2017) showed that the presence of positive verbal feedback from the employer to the worker, when associated with a relatively high wage, has a positive effect on workers' effort provision. We complement this literature by showing evidence of moral support as an effective nonmonetary incentive in a highly competitive labor environment with high monetary incentives in place. In particular, our results can offer a possible explanation of the results found by Kassis et al. (2021). They showed that teams whose captains can decide about the penalty shooting sequence are more likely to win the shootout, but they are unable to identify a particular mechanism for this. If winning a coin toss is perceived as a moral boost that increases self-confidence and performance, then our paper can provide a mechanism consistent with their findings.

Finally, this paper contributes to the economics literature using sports data to understand human behavior (see Palacios-Huerta 2014 for an excellent review). Apesteguia and Palacios-Huerta (2010) used data on football penalty kicks to identify the effect of psychological pressure on the probability of scoring, depending on the order of the kicks.[2] Feri et al. (2013) found that the effect of psychological pressure in competitive environments is moderated by individual differences on cognitive anxiety. Related to this literature, this paper provides clean evidence of how moral support contributes to a well-established phenomenon in the sports economics literature: home advantage. Home advantage refers to a greater success rate in home versus away competitions. It is a robust phenomenon that has been consistently highlighted in sports competitions both individually (see, e.g., Koning 2011) and on teams (see, e.g., Gómez and Pollard 2011, Liardi and Carron 2011, Priks 2013, and Peeters and van Ours 2021).[3] According to this literature, the main reasons for the existence of home advantage are familiarity with the context, travel fatigue, territoriality, and referee bias caused by the pressure of the crowd. Garicano et al. (2005) showed that social pressure biases football referees toward home teams.[4] We show that this channel does not seem to play a role in the context of our study.

Recently, because of the COVID-19 pandemic, there has been a proliferation of studies on home advantage, exploiting the opportunity represented by the complete lack of supporters in football stadiums. The general finding reinforces the existence of home advantage because of referee bias as a consequence of social pressure (Cueva 2020, Dilger and Vischer 2020, Endrich and Gesche 2020, Ferraresi and Gucciardi 2020, Bryson et al. 2021, Fischer and Haucap 2021, Scoppa 2021, Sors et al. 2021, Cross and Uhrig 2023). We believe that compared with the COVID-19 shock in European football leagues, the exogenous change we exploit in Argentina offers a cleaner identification of a pure shock on moral support. First, COVID-19 not only affected the presence of people in stadiums but also changed a multiplicity of factors that could affect team performance. Second, COVID-19 affected the presence of supporters of home and visitor teams alike. Banning all supporters can have differential effects on home and visiting teams, and therefore, the marginal effects on the final score (or likelihood of winning) might be confounded by an inability to identify the effects of moral support for home and visiting teams separately. In contrast, the Argentinean shock affected only the number of supporters of the visiting teams, which sharpens the identification of the change in moral support. Finally, the universality of the COVID-19 shock does not allow the presence of a contemporaneous counterfactual. In the case of Argentina, we exploit the fact that the ban on the visiting team was only for *League* games and not for *Copa Argentina* games, which we use as a counterfactual experiment.

Our result that, on average, visiting teams are about 20% (8 percentage points; 0.18 standard deviation) more likely to lose without the presence of their supporters is sizable, but consistent with recent literature reporting that when no supporters are allowed (for example, due to Covid-19), home teams win less often.[5] That is, having a crowd in the stadium (which is almost always leaning more heavily toward the home team) seems to contribute to the well-known home advantage in football. This paper goes one step further by showing, with a cleaner natural experiment than Covid-19, what happens when there is a crowd, but no supporters of the visiting team are admitted. By the logic of the home advantage in response to having an audience, one would expect an even stronger home advantage when visiting teams' supporters are banned, and this is exactly what this paper shows.[6]

2. Context and Data

2.1. Context

Ever since the conception of professional football in Argentina in 1931, violence around football games has been a constant problem for the country. According to the NGO "Salvemos al Fútbol," to date, 334 people have died because of violent episodes at Argentinean football games. Despite the implementation of different safety measures, such as increasing the number of police agents at games or installing security cameras in the stadiums, the magnitude of the problem has only worsened with time. Excluding the massive tragedy of 1968 during a River Plate vs. Boca Juniors game,[7] the overall trend over the past century indicates an increasing number of deaths, achieving its maximum in the triennium 2012−2014. Figure A.1 in the Online Appendix reports the evolution of the number of victims in Argentinean football from 1934 to 2014.

June 10, 2013 marked a turning point in the history of Argentinean football. During the first-division (Primera División) game between Club Atlético Lanús and Estudiantes de La Plata, a Lanús supporter was killed by a police rubber bullet shot. Following this incident, the AFA (Asociación de Fútbol Argentino), together with the A.Pre.Vi.De (Agencia Prevención Violencia en el Deporte), decided to implement a drastic measure in order to limit violence. This took the form of a ban forbidding the presence of visiting team supporters during first-division games. It was immediately effective until the end of the 2012−2013 season, and it was subsequently extended for the following seasons (Act: 4810, August 20, 2013). Only home team supporters could enter the stadium, whereas the visitors' stand had to remain empty.

In 2015, the government occasionally lifted the ban for some selected games as a pilot experiment. The ban is still in place to date (as of December 2022), but since 2015, besides the nonrandom temporary lifting of the ban in different forms, and besides COVID-19, there were also a series of nonrandom structural changes in the organization of the first division of the Argentinean football. All the changes that occurred since 2015 were nonrandom and most likely were the outcome of political negotiations among the first-division clubs. For these reasons, the only clean setting for identification purposes took place between June 2013 and December 2014, which is the period that we cover in this paper. Adding games played after December 2014 would pollute our identification.[8]

2.2. Data

To assess the impact of the ban on visiting teams' performance, we collected data from the Argentinean first-division games played between August 2011 and December 2014.[9] Our primary source of data is the popular football website transfermarkt.com.[10] Transfermarkt contains scores, results, and rankings of numerous leagues globally as well as information on companies, players' careers, and transfers. As shown by Frick and Prinz (2006), Bryson et al. (2013), and Peeters (2018), estimated players' values are extremely accurate and take into account salaries, signing fees, bonuses, and transfer fees (Franck and Nüesch 2012).

Our main data set contains information on 25 teams and 1,330 games: 380 games for each of the first three seasons (2011−2012, 2012−2013, 2013−2014) and 190 games for the 2014 season.[11] Using the exact date of each game, we divided the sample into 591 "treated" games played after the implementation of the ban and 739 "control" games played before the ban. For each game, we consider the final result, the number of goals scored by each team, the number of yellow and red cards given to players of each team, and penalties conceded.[12] We observe team lineup at each game, including information on all of the players that were on the game roster. Furthermore, we retrieve information on the entire squad value at the beginning of each season.[13]

In addition, we also scraped data on the national cup (*Copa Argentina*) games that were played in the same period of the study.[14] The ban did not apply to the *Copa Argentina* games, which makes these games an informative counterfactual group. However, this additional data set contains only 161 games, and the teams are often not the same as those playing in the main league. This limitation makes the sample not suitable for a robust difference-in-difference specification. Therefore, we use these data only as a robustness check. For the *Copa Argentina* games, we are able to record only the final results.

Panel A of Table 1 presents summary statistics of the variables used for the main analysis. For each variable, the table reports its mean and standard deviation before and after the ban. The last row shows the number of games in our database. Notice that visiting teams are more likely to lose than home teams both before and after the ban. This is the so-called "home advantage." What is key to this paper is that the probability of losing for a visiting team is higher after the ban. Indeed, visiting teams are more likely to lose, less likely to draw, and, to a lower extent, less likely to win after the ban. Online Appendix Figure B.1 contains a graphical representation

Table 1. Summary Statistics

	Before		After	
	Mean (1)	SD (2)	Mean (3)	SD (4)
Panel A: League games				
Visiting team losing (share)	0.403	0.491	0.462	0.499
Visiting team winning (share)	0.261	0.440	0.250	0.434
Draws (share)	0.336	0.473	0.288	0.453
Score difference (HT-VT)	0.269	1.458	0.391	1.524
Goals scored by home team	1.231	1.116	1.335	1.147
Goals scored by visiting team	0.962	0.986	0.944	1.004
Red Cards to home team	0.173	0.420	0.141	0.394
Red Cards to visiting team	0.251	0.519	0.222	0.537
Yellow cards to home team	2.350	1.335	2.215	1.349
Yellow cards to visiting team	2.797	1.432	2.666	1.324
Number of penalties awarded home team	0.107	0.326	0.141	0.376
Number of penalties awarded visiting team	0.061	0.239	0.080	0.271
Number of games	739		591	
Panel B: Cup games				
Visiting team losing (share)	0.453	0.500	0.491	0.505
Visiting team winning (share)	0.425	0.497	0.509	0.505
Draws (share)	0.123	0.330	0.000	0.000
Number of games	106		55	

Notes. This table reports the summary statistics of the data set we use for the main analysis (league games) in panel A and for the counterfactual analysis (cup games) in panel B. Columns (1) and (3) report the average values before and after the ban, and Columns (2) and (4) report the standard deviations. "Visiting team losing (share)" refers to the proportion of games that ended with a victory for the home team. "Visiting team winning (share)" refers to the proportion of games that ended with a victory for the visiting team. "Draws (share)" refers to the proportion of games that ended with a draw. "HT-VT" refers to the difference between the goals scored by the home team (HT) and the goals scored by the visiting team (VT).

of change in the probability of losing for the visiting team. It plots the portion of games ended with a defeat of the visiting team in the 59 turns (match day) played before and after the ban. In addition, it shows the linear fit using all the observations before and another using the after-ban games. From the figure, it is clear that (a) there is a clear jump in the share of games lost by the visiting team after the introduction of the ban to visiting team supporters and (b) there is no upward or downward trend in the outcome variable.[15] The score differences in favor of home teams also increase, resulting mainly as a consequence of the number of goals conceded to visiting teams. The table also shows that, in line with "home advantage," referees are more likely to award more penalties to home teams and to give more red and yellow cards to visiting teams. It is important to note that this figure only slightly changes with the ban.

Panel B of Table 1 refers instead to the national cup games that we use in our counterfactual analysis. In this case, both the fraction of visiting teams losing and winning increased after the ban. Contrary to what happens in league games, the net change is in favor of the local team rather than the visiting team.

3. Impact Estimates

3.1. Empirical Model

The aim of this study is to identify the effect on team performance of switching from playing a football game as the visiting team in a stadium with both home and visiting team supporters versus playing a football game as the visiting team in a stadium with only home team supporters. The latent variable is the overall performance of visiting teams. As a proxy for team performance, we use the result of the game and the score difference, calculated as the difference between the number of goals scored by the home team and the goals scored by the visiting team. We estimate two models: a linear probability model, where the dependent variable indicates games ended with the visiting team losing, and an ordered logit model for the score difference. In both specifications, the dependent variable is regressed on team and game fixed effects and on a dummy variable indicating whether the game was played with or without supporters. Our main specification is

$$y_{it} = \alpha + \beta L_{it} + \gamma_i + \varepsilon_{it}, \tag{1}$$

where y_{it} is a dummy that takes value 1 if the visiting team lost the game, or match, i that was played in week t; α is a constant, and L_{it} is a dummy taking value 1 when the ban is in force.[16] The variable γ_i indicates time-invariant unobserved components related to the intrinsic characteristics of the teams or the games; we estimate different specifications, including (i) home team fixed effects, (ii) visiting team fixed effects, (iii) home and visiting team fixed effects, and (iv) match fixed effects. In this way, we assure that any significant estimated effect for the coefficient of interest (β) is not driven by specific team pairs. To control for potential autocorrelation of the error terms, we cluster standard errors at team and match level.[17]

Our empirical model essentially compares the results of the games in the Argentinean first league played before the ban to results of games played after the ban was introduced. The identification assumption relies on the nonexistence of other forces that could affect the result of the games and appear contemporaneously with the ban or in the period just after. In other words, we assume that the expected result of every game played before the day in which the law took effect and after that day would be the same if the ban had never been implemented.

In addition to including season and round fixed effects to control for heterogeneity within a season and round and also to controlling for different time trends, in Sections 3.3 and 3.4 we perform two additional analyses to sharpen our identification. We first conduct a counterfactual test using the games from the national cup tournament (*Copa Argentina*) instead of the league games. The national cup is played every year by teams from first and lower divisions of the AFA, and it fits as a counterfactual experiment because the ban for visiting team supporters does not apply to the cup, and plus the games were played contemporaneously to the first-division league. Second, we replicate the main analysis dropping the games played by teams that were promoted or relegated in 2013 and those played by teams that did not participate in all four seasons.

3.2. Main Result: Effect on Team Performance

Table 2 reports the coefficients of estimating Equation (1) with OLS for alternative specifications. The specification in Column (1) shows estimates without any control variables. The probability that the visiting team loses a game in the period in which the law is in effect is, on average, 6.3 percentage points greater than before, equivalent to an increase of 15.64%. Columns (2) to (4) report OLS estimates of Equation (1), with standard errors clustered by team (visiting or home) and by game, respectively. The main result holds for these different specifications. In the remaining columns, we add home team fixed effects (Column 5), visiting team fixed effects (Column 6), both (Column 7), and game fixed effects (Column 8). In these last four specifications, the size of the coefficient of interest only increases.

Our preferred specification is reported in Column (6), where we control for visiting team fixed effects, because all of the unobservable time-invariant components related only to the visiting team are taken into account. In this specification, the ban increases the probability of losing a game for the visiting team by 21.6% (0.18 standard deviation increase).

Table 2. Effects of the Ban on the Probability of Losing as a Visitor

	OLS estimation							
Dependent variable: *dummy for losing/not losing a match for the visiting team*								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Presence of the ban	0.059**	0.059**	0.059*	0.059**	0.046*	0.087***	0.075**	0.081*
	(0.027)	(0.026)	(0.029)	(0.027)	(0.024)	(0.029)	(0.031)	(0.041)
Dummies home team					✓		✓	
Dummies visiting team						✓	✓	
Dummies match								✓
N	1,330	1,330	1,330	1,330	1,330	1,330	1,330	1,330
Number of clusters		25	25	550	25	25	550	550
Cluster home team		✓			✓			
Cluster visiting team			✓			✓		
Cluster match				✓			✓	✓

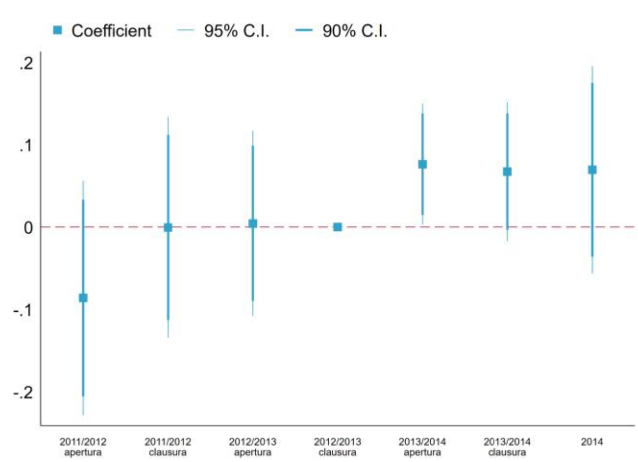
Notes. OLS estimation of the effect of the ban on the probability of losing a game for the visiting team. Controls include dummies for home team in Columns (5) and (7), dummies for visiting team in Columns (6) and (7), and dummies for game in Column (8). Beta-coefficients reported and robust standard errors in parentheses. Standard errors are clustered by home team in Columns (2) and (5), by visiting team in Columns (3) and (6), and by game interaction in Columns (4), (7), and (8).
***Significant at 1%; **significant at 5%; *significant at 10%.

Online Appendix Table C.1 shows that these results are robust for using a Logit model. Online Appendix Table C.2 replicates the analysis using two-way clustered standard errors, where indicators for the home and the visiting team represent the two cluster dimensions. The table shows that results remain stable. Online Appendix Tables D.1–D.3 show that results remain stable to the inclusion of turn (time) linear, quadratic, and cubic trends, respectively. The magnitude of the effect is consistent with the main result reported above, and it is constant in time. Because there are only 190 binary observations in each half-season bin, standard errors are larger. Finally, to alleviate any possible remaining concerns regarding potential trends, following Goodman-Bacon (2021), we estimate a pre-trend based on the data before the ban, compute the residuals, and re-estimate the baseline model on these residuals. Results of the first and second stage of this analysis are presented in Online Appendix Table D.4. As can be observed, our results are robust for this approach.

For completeness, we estimate the event study version of the previous model.[18] The accident that generated the ban happened toward the end of the 2012−2013 *Clausura* season. Therefore, we use that half-season as a reference and estimate six coefficients representing the change in the probability of losing for the visiting team in the three half-seasons before and in the three half-seasons after the 2012−2013 *Clausura* one. We report these estimates in Figure 1. As expected, the figure shows no significant differences in the probability of losing among the four half-seasons before the ban, whereas it highlights a significant increase in this probability in the two subsequent half-seasons. The result for the half-season 2014 is not significant but in terms of magnitude is in line with the previous two.

In addition, we study the effect of the ban on another proxy of relative team performance: the difference between the number of goals scored by the home team and the number of goals scored by the visiting team. We refer to this measure as "score difference." The specification that we use is the same as that described in Equation (1). As a dependent variable we use the score difference instead of a dummy for the visiting team losing. Table 3 reports the estimated coefficients of an ordered logit model on the effect of the ban on the score difference. As before, our preferred specification is in Column (6), where dummies for the visiting team are included, and standard errors are clustered at the visiting team level. As is evident from the table, we find that the odds that the visiting team concedes an additional goal more than the opponent are 1.3 times greater after the ban.

Figure 1. (Color online) Event Study Coefficients



Notes. This figure plots OLS estimation coefficients of the effect of the half-season dummies on the probability of losing a game for the visiting team. The *2012−2013 Clausura* half-season dummy is taken as reference point and is omitted from the regression. Controls include dummies for the visiting team. Standard errors are clustered by local and visiting team.

Table 3. Effects of the Ban on the Score Difference

Maximum-likelihood estimation								
Dependent variable: *goals difference in the final result*								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Presence of the ban	1.184*	1.184*	1.184*	1.184*	1.165	1.302**	1.292**	1.371*
	(0.117)	(0.114)	(0.115)	(0.117)	(0.114)	(0.136)	(0.154)	(0.229)
N	1,330	1,330	1,330	1,330	1,330	1,330	1,330	1,330
Number of clusters		25	25	550	25	25	550	550
Cluster home team		✓			✓			
Cluster visiting team			✓			✓		
Cluster match				✓			✓	✓

Notes. Maximum-likelihood estimation of an ordered logit model of the effect of the ban on the goals difference. Goals difference is computed by subtracting the number of goals scored by the visiting team from the number of goals scored by the home team. Controls include dummies for home team in Columns (5) and (7) and dummies for visiting team in Columns (6) and (7). Beta-coefficients reported and robust standard errors in parentheses. Standard errors are clustered by home team in Columns (2) and (5), by visiting team in Columns (3) and (6), and by game interaction in Columns (4) and (7).

***Significant at 1%; **significant at 5%; *significant at 10%.

In the Online Appendix (Table E.1), we study the effect of the ban on the absolute number of goals scored by each team separately. We find that the ban significantly increases the number of goals scored by home teams (Panel A, column 6) but does not affect the number of goals scored by visiting teams (Panel B, column 6). This implies that the observed score difference is due to the home teams scoring more rather than the visiting teams scoring less.

3.3. Counterfactual Experiment

The ideal counterfactual group for our empirical analysis would be one in which the same teams play contemporaneously to the period we use for the analysis but in a context in which the ban is not in effect. Fortunately, the Argentine case provides a setting that is close to this ideal. We exploit the fact that the AFA did not implement the ban for games played in the contemporaneous tournament, *Copa Argentina*.[19] This constitutes a valid counterfactual because these are games played in the same time period as those of the League by most of the teams of the League but with the visiting supporters being allowed to enter the stadiums. To test whether the ban had an effect on the probability of losing a game as a visiting team, we estimate Equation (1) using games played for the *Copa Argentina* instead of games played in the League.

Table 4 presents the results of this counterfactual experiment. The main coefficient is never statistically significant, and in the first four columns, without fixed effects, it is also small in magnitude. Only for consistency with previous tables, we include regressions with team and match fixed effects (columns (5)−(7)). However, these coefficients are not well identified because of the low number of games played in the national cup and because of the variability in the teams; each team appears on average 2.78 times in the sample, and only 29 teams played at least a game before and after the ban. Whereas, as previously mentioned, this limitation makes the Cup Games sample not suitable for a robust difference-in-difference estimation, it does provide a close to ideal counterfactual.[20]

3.4. Excluding Promoted, Relegated Teams, Lanús and Estudiantes

The implementation of the ban started two weeks before the end of 2012−2013 season and the beginning of 2013−2014 season. As mentioned in Section 2.2, there were no changes in the league structure or in the rules from one season to another. However, three teams, *Independiente, Union de Santa Fé*, and *San Martín de Tucumán*, got relegated to the second division, whereas three other teams, *Olimpo de Bahía Blanca, GELP*, and *Rosario Central*, were promoted to the first division. These two groups of teams may differ in ways that are correlated with our dependent variable. Indeed, they do differ in the geographical position of their stadium and the average number of visiting supporters. To account for this concern, on top of including team fixed effects, we run as a robustness check the main specification excluding all games played by these six teams. As shown in Online Appendix Table F.1, our main results remain robust for this restriction.

As an additional robustness check, we perform the same analysis excluding all teams that were promoted or relegated at least once in the study time span, restricting the sample to the 12 teams that participated in all of the seasons.[21] Again, as Online Appendix Table F.2 shows, our results are not sensitive to this sample selection.

Finally, we account for potential bias in the results coming from the team that were the cause for the ban, and we replicate the main result, excluding the games played by *Lanús* and *Estudiantes*. We report results in Online Appendix Tables F.3 and F.4 and show that the main results are also robust for this exercise.

Table 4. Counterfactual Test: Main Regression Specifications with Cup Games

OLS estimation							
Dependent variable: *=1 if visiting team loses*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Presence of the ban	0.038	0.038	0.038	0.038	−0.038	0.123	0.202
	(0.083)	(0.080)	(0.083)	(0.084)	(0.112)	(0.135)	(0.254)
Dummies home team					✓		✓
Dummies visiting team						✓	✓
N	161	161	161	161	161	161	161
Number of clusters		58	74	160	58	74	160
Cluster home team		✓			✓		
Cluster visiting team			✓			✓	
Cluster match				✓			✓

Notes. OLS estimation of the effect of the ban on the probability of losing a game for the visiting team. Sample: all games of the *Copa Argentina* between August 2011 and December 2015. Controls include dummies for home team in Columns (5) and (7) and dummies for visiting team in Columns (6) and (7). Beta-coefficients reported and robust standard errors in parentheses. Standard errors are clustered by home team in Columns (2) and (5), by visiting team in Columns (3) and (6), and by game interaction in Columns (4) and (7).
***Significant at 1%; **significant at 5%; *significant at 10%.

4. Mechanisms

In this section, we consider alternative channels, other than moral support, through which the ban could potentially affect visiting team performance. In particular, we study the effect of the ban on referee hostility, manager strategy, and player value. We finish this section by studying differential effects of the ban for big and small clubs.

4.1. Does the Ban Affect Referees' Behavior?

Lack of supporters could in principle affect the performance of visiting teams by increasing referee hostility toward them. There is evidence showing that referees can bias their decisions because of supporters' pressure (Sutter and Kocher 2004, Garicano et al. 2005). The lack of visiting supporters might alleviate that pressure and increase referee hostility toward visiting teams. In this subsection, we investigate whether such mechanism is at work in our setting.

Referees can influence the result of a game by awarding penalties or giving yellow and red cards[22] to players in an unfair way Boyko et al. (2007).[23] We test whether the ban increased the hostility of referees toward visiting teams by estimating Equation (1) using as outcome variables the number of yellow and red cards given to players as well as the number of penalties inflicted on home and visiting teams.

Results of OLS estimations are presented in Table 5; panel A shows the effect of the ban on yellow cards, panel B on red cards, and panel C on penalties. Some specifications point toward a significant reduction of yellow cards awarded to both home and visiting teams after the ban. These effects always go in the same direction for both teams and are very similar in terms of magnitude and are never significantly different from each other. Regarding penalties, we observe some slight increase in the penalties awarded to home teams but also to visiting teams after the ban. A t-test reveals that the increase in penalties awarded to home teams is not significantly different from the increase in penalties awarded to visiting teams (with p values ranging from 0.525 to 0.533, depending on the specification).[24]

We further replicate the main analysis controlling for yellow and red cards awarded to each team in Online Appendix Table G.1, penalties awarded to each team in Online Appendix Table G.2, and both in Online Appendix Table G.3. All results remain significant. The magnitude of the effect decreases by very little, signaling that a tiny portion (1% to 5%) of the total effect that we identify might be due to changes in referee behavior. All in all, the analysis suggests that there is no strong evidence of a change in referee hostility toward one of the two teams. Hence, we conclude that the reduction in visiting team performance cannot be attributed to this a priori plausible mechanism.

4.2. Does the Ban Change the Strategy of Managers?

Another potential confounding factor that could be affected by the presence of the ban regards the strategy of managers. In principle, managers could internalize that without the support when playing away, they would be more likely to lose and adapt their strategy accordingly. In addition, because the ban does not apply to nonleague games, managers could decide to change the distribution of energy between home games and away games when playing in the league or in the cup, and this could be a potential confounding factor threatening identification.

In order to test this potential mechanism, we perform two sets of analyses. First, we include different sets of time controls. We estimate our main specification with

Table 5. Effect of the Ban on Referees' Decisions

	OLS estimation							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Yellow cards								
Dependent variable: *number of yellow cards shown to home team players*								
Presence of the ban	−0.134*	−0.134	−0.134*	−0.134*	−0.139	−0.128	−0.134	−0.160
	(0.074)	(0.082)	(0.076)	(0.071)	(0.093)	(0.086)	(0.083)	(0.111)
Dependent variable: *number of yellow cards shown to visiting team players*								
Presence of the ban	−0.131*	−0.131	−0.131	−0.131*	−0.169*	−0.082	−0.121	−0.077
	(0.076)	(0.083)	(0.095)	(0.076)	(0.088)	(0.094)	(0.086)	(0.118)
Panel B: Red cards								
Dependent variable: *number of red cards shown to home team players*								
Presence of the ban	−0.033	−0.033	−0.033	−0.033	−0.035	−0.037	−0.038	−0.043
	(0.022)	(0.022)	(0.025)	(0.022)	(0.022)	(0.027)	(0.025)	(0.034)
Dependent variable: *number of red cards shown to visiting team players*								
Presence of the ban	−0.029	−0.029	−0.029	−0.029	−0.026	−0.009	−0.006	−0.022
	(0.029)	(0.029)	(0.026)	(0.028)	(0.032)	(0.032)	(0.034)	(0.042)
Panel C: Penalties awarded								
Dependent variable: *number of penalties awarded - home team*								
Presence of the ban	0.034*	0.034	0.034	0.034*	0.033	0.035	0.034	0.028
	(0.020)	(0.023)	(0.020)	(0.019)	(0.027)	(0.023)	(0.023)	(0.030)
Dependent variable: *number of penalties awarded - visiting team*								
Presence of the ban	0.019	0.019	0.019	0.019	0.017	0.019	0.017	0.012
	(0.014)	(0.012)	(0.013)	(0.014)	(0.014)	(0.013)	(0.017)	(0.023)
Controls								
Dummies home team					✓		✓	
Dummies visiting team						✓	✓	
Dummies match								✓
N	1,328	1,328	1,328	1,328	1,328	1,328	1,328	1,328
Number of clusters		25	25	550	25	25	550	550
Cluster home team		✓			✓			
Cluster visiting team			✓			✓		
Cluster match				✓			✓	✓

Notes. Panel A: OLS estimation of the effect of the ban on the number of yellow cards shown to home/visiting team players. Panel B: OLS estimation of the effect of the ban on the number of red cards shown to home/visiting team players. Panel C: OLS estimation of the effect of the ban on the probability of having a penalty awarded to the home/visiting team. Controls include dummies for home team in Columns (5) and (7), dummies for visiting team in Columns (6) and (7), and dummies for game in Column (8). Beta-coefficients reported and robust standard errors in parentheses. Standard errors are clustered by home team in Columns (2) and (5), by visiting team in Columns (3) and (6), and by game interaction in Columns (4), (7), and (8).

***Significant at 1%; **significant at 5%; *significant at 10%.

half-season fixed effects (apertura/clausura) and turn/week fixed effects (from 1 to 19). In this way, every single turn/week within a season is compared with the correspondent turn/week in other seasons. We also estimate Equation (1) adding month fixed effects (from 1 to 12) to compare all games played in a particular month of the year. Online Appendix Tables H.1 and H.2 report results of this analysis. All the coefficients of interest remain significant. The magnitude of the effect is approximately the same as in the basic model of Table 2 for the first specification, whereas it increases by 1% in the second model. These results rule out any potential change in visiting teams' performance that could happen because of time, other than the ban.

Second, we test whether there is a difference between home and away lineups of the same team and how this changed after the ban, irrespective of the market value. We define the team's lineup of a game as the set of the 11 starting players. We do a bilateral comparison of each team's lineup with every other lineup of the same team within a half-season.[25] For each lineup pair, we compute the Jaccard similarity index (Jaccard 1908), which is defined as the quotient of the intersection between two sets divided by their union. The index takes values between zero (completely different lineups) and one (identical lineups). After making every within-team bilateral comparison of lineups for each half-season, we end up with 38 Jaccard indexes per game, 19 for the home team and 19 for the visiting team, for a total of 7.600 indexes per half-season.[26] Because each lineup can refer to either a home or an away game, we have four types of lineup pairs: (i) home-home, (ii) home-visiting, (iii) visiting-home, and (iv) visiting-visiting. We then average all of the indexes in each of the four groups and test whether there are differences between these four statistics and whether these differences change with the ban.

Figure 2 shows the averages Jaccard indexes for home team (panel (a)) and visiting team (panel (b)) lineups for each half-season. The blue dots refer to similarity with the other home games and the red dots to similarity with the away games. We do not find any significant difference in the similarity index between home and visiting lineups. We find instead that each home game lineup is slightly more similar to the lineups of the other games when the team plays visitor than the ones of the other home games. A mirrored pattern arises when observing the lineups when the team plays away. This is not surprising if we take into account that there is usually an alternation between home games and games as visitor, making all home games closer in time to the visiting games than the home games and vice-versa. More importantly for the main goal of the analysis, we do not find any sign of changes in the similarity structure after the ban. If managers changed their strategy after the ban by choosing different players for home and away games, we would observe an inverse position of the blue and the red dot after the 2012−2013 season, which is clearly not the case.

We also use the Jaccard similarity index as a control in our main Equation 1 to study (a) whether our main results hold and (b) whether changes on team lineups impact the likelihood that a visiting team loses a game. Online Appendix Table H.3 reports results of the estimation for the eight specifications. The set of control variables includes all possible combinations of the Jaccard index between home (visiting) teams and home (visiting) games. The number of observations decreased to 1,309 games because the starting lineup of 11 players was not available for 21 games. As expected, our main result is robust for this new specification. Given the similarity in the Jaccard index between the lineups for home and visiting games reported in Figure 2 and considering the results of the regressions reported in Online Appendix Table H.3, we conclude that managers did not react to the ban by strategically modifying player lineups when playing home or away.

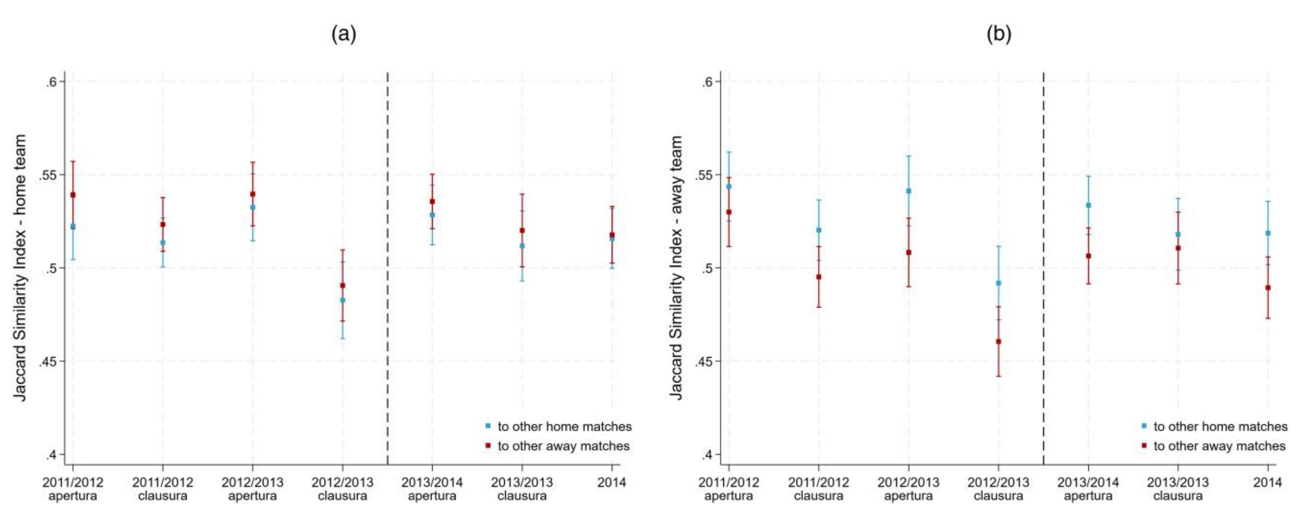
4.3. Does the Ban Affect the Market Value of Teams?

The presence of the ban could potentially affect the market value of teams. For instance, teams may be motivated to sell some of their top players to foreign leagues as a way to compensate for the reduction in the seasonal income because of the lack of visiting supporters at the stadium. This would imply an average decrease in the market value of teams between the end of 2012−2013 season and the beginning of 2013−2014 season, with potential consequences on team performance. To test for this potential channel, we analyze player monetary value using data from Transfermarkt.[27] Transfermarkt estimates the value of most (professional) football players in the world and constantly updates the database, taking into account salaries, bonuses, and transfer fees.[28]

Figure 3 shows the evolution of the average player market value by season. In the left panel we represent the average value of all teams playing in the first division, whereas in the right panel we separate the analysis between the *Big-5* clubs, reported in red, and all the teams together, reported in blue.[29]

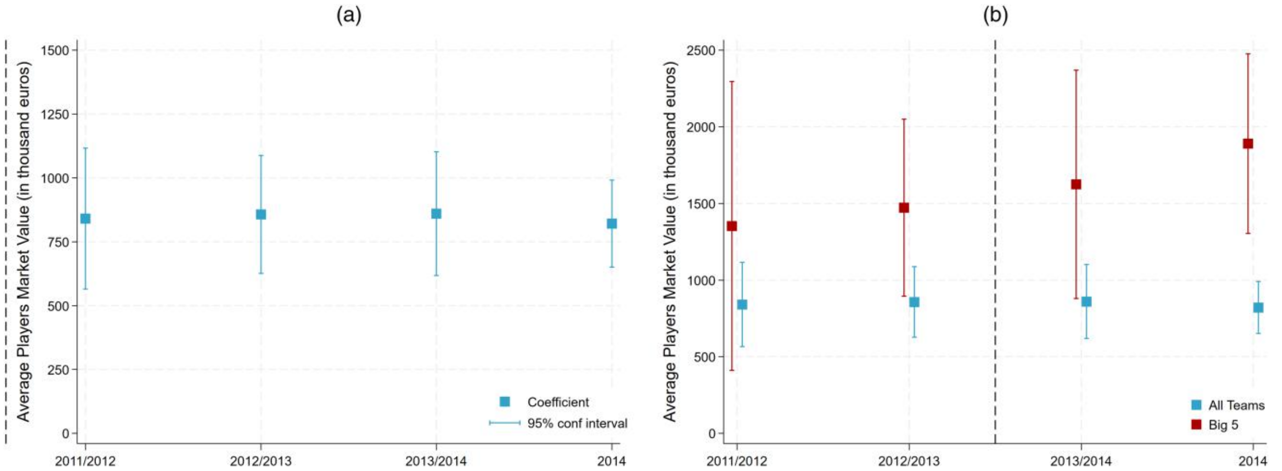
We divide the teams into two groups because if there is an effect on market value we believe that it should be

Figure 2. (Color online) Jaccard Similarity Index



Notes. Panel (a): lineups of home teams. Panel (b): lineups of visiting teams. This figure shows the average lineup Jaccard similarity index for home team (panel a) and visiting team (panel b) by half-season. The sample includes 1,309 games, for which Transfermarkt reports exactly 11 starting players for each team.

Figure 3. (Color online) Average Player Values by Season



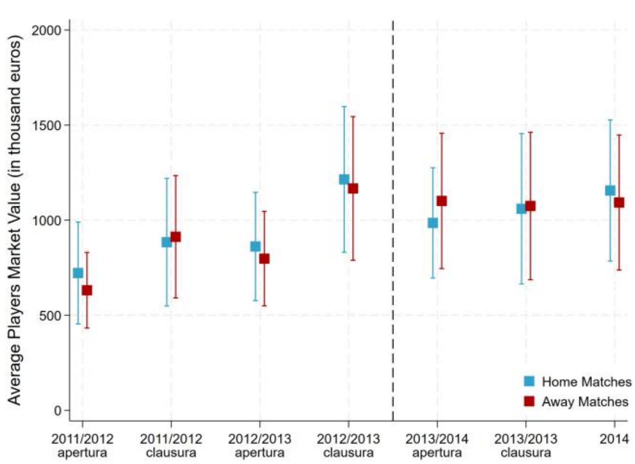
Notes. Panel (a): all teams. Panel (b): Big 5 vs. the rest. This Figure shows the average value of all players playing in the First Argentinean League by season. Note that the sample includes all 820 of the players reported in the Transfermarkt database with a player value greater than 0.

more salient for bigger teams, which have more top-value players. In the left panel of Figure 3, we observe that the average value of players does not change substantially between seasons when considering all of the teams in the analysis, ruling out any possibility of *fire-sell* because of the loss of income after the ban. In the right panel of Figure 3, not surprisingly, we observe that the average market value for the *Big-5* is, for each season, much higher compared with the average of all teams together. Interestingly, the presence of the ban does not have a negative effect on the market value of the *Big-5*, which keeps following a slightly increasing trend toward all the seasons.

Even if the total value of the team remains constant, the value of the lineups could change between games, depending on which players the manager chooses. Following the same argument in Section 4.2, managers could decide strategically to play with better players (i.e., more valuable) in home games, given the presence of team supporters, while not employing the most valuable players in the starting lineup when playing away.[30] Figure 4 reports the average player market value for the seven half-seasons separately for home (in blue) and away (in red) games. The vertical dotted line represents the introduction of the ban occurring between the end of the 2012−2013 season and the beginning of the 2013−2014 season. Despite a mild, not significant, increase in the lineups' value in the first three seasons, we do not record any change between the last pre-ban season and the following ones. As expected, there are no differences between the value of the teams for home versus away games and no change after the ban.

As in the previous section, we replicate the main estimation, controlling for the average seasonal market value of home and visiting teams. As shown in Online Appendix Table H.4, in all of the specifications, the coefficients for the market value of home teams are positive and statistically significant, implying an increase in the probability that a visiting team will lose if the market value of the home team increases. The opposite occurs when the market value of the visiting team increases given that the probability that the visiting team will lose decreases significantly. Because, as shown above, the team value does not change between seasons, controlling for team fixed effect makes these coefficients not significant. In all specifications, our main coefficient of interest remains positive and significant after controlling for team value. Thus, we can conclude that the negative effect of the ban on visiting team performance is not due to changes in team market value.

Figure 4. (Color online) Average Player Values by Half-Season



Notes. This figure shows the average value of all players playing in the Argentine First League by half-season. The sample includes all of the 467 players reported in the Transfermarkt database with a player value greater than 0 that played at least one game in the starting 11.

4.4. Does the Ban Affect the Revenues of the Visiting Teams?

A potential alternative mechanism behind our results could be that visiting teams perform worse after the ban because their revenues are cut, because their supporters could not buy tickets when they play away. Although we do not have data on revenues, the way Argentine football is organized makes this alternative mechanism implausible. All revenues from the sales of tickets of a game are accrued by the host team, and the costs to organize the game are also paid exclusively by the host team. The guest teams do not get any revenue from the tickets bought by their supporters when they play away.

5. Heterogeneous Treatment Effect

In this section, we analyze whether the lack of moral support is more consequential for bigger or smaller clubs. A priori, it is not clear what to expect. Although bigger clubs may be more affected by the ban because they have more supporters, they also have more monetary resources and hence, may rely less on the moral support of their fans. Smaller clubs may instead rely more on their supporters to compensate for the lack of monetary resources.

To answer this question, we leverage that the Argentinean football league has a recognized clear distinction between the five biggest clubs and the rest. The biggest clubs, called "*the Big 5*" (los cinco grandes), are Boca Juniors, River Plate, San Lorenzo, Racing Club, and Independiente. These clubs have by far the largest number of supporters, the highest number of members, and the highest number of followers on social media. They manage the biggest budgets and have won the most national and international cups (AFA—FIFA - Informe Clubes Fútbol 2019).[31] We refer to all the other teams that are not in the *Big 5* circle as *small* clubs.

To test whether the ban affected the *Big 5* clubs more than the smaller clubs, we augment the model in Equation (1) by binary variables for home and visiting team being a *Big 5* and interactions with the ban indicator,

$$y_{it} = \alpha + \beta L_{it} + \delta_1 B5H_i + \delta_2 B5V_i + \delta_3 B5H_i \times B5V_i + \psi_1 L_{it} \times B5H_i + \psi_2 L_{it} \times B5V_i + \psi_3 L_{it} \times B5H_i \times B5V_i + \gamma_i + \varepsilon_{it} \quad (2)$$

where y_{it}, L_{it}, and γ_i are the indicators for the visiting team losing, the ban, and the game time invariant controls, respectively, as described in Equation (1). $B5H_i$ and $B5V_i$ are binary variables for home (H) and visiting (V) team being a *Big 5*.

Table 6 reports the results of this analysis for all the specifications, whereas Online Appendix Figure I.1 reports a graphical representation of the estimated coefficients for

Table 6. Heterogeneous Effects: The *Big-5*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OLS estimation							
Dependent variable: *=1 if visiting team loses*							
Presence of the ban	0.071**	0.071**	0.071*	0.071**	0.059*	0.105**	0.094**
	(0.035)	(0.032)	(0.038)	(0.033)	(0.032)	(0.038)	(0.037)
Visiting team Big 5	−0.037	−0.037	−0.037	−0.037	−0.037		
	(0.048)	(0.032)	(0.046)	(0.045)	(0.033)		
Home team Big 5	0.060	0.060	0.060	0.060		0.063	
	(0.049)	(0.052)	(0.061)	(0.050)		(0.061)	
Visiting team Big 5 * ban	−0.120*	−0.120**	−0.120**	−0.120*	−0.121**	−0.129**	−0.129*
	(0.071)	(0.057)	(0.056)	(0.071)	(0.058)	(0.049)	(0.074)
Home team Big 5 * ban	0.026	0.026	0.026	0.026	0.016	0.019	0.008
	(0.074)	(0.070)	(0.088)	(0.079)	(0.064)	(0.087)	(0.082)
Visiting big 5 * home Big 5	−0.036	−0.036	−0.036	−0.036	−0.040	−0.039	−0.043
	(0.109)	(0.058)	(0.067)	(0.096)	(0.061)	(0.066)	(0.094)
Visiting big 5 * home Big 5 * ban	0.200	0.200**	0.200	0.200	0.210**	0.200	0.209
	(0.166)	(0.087)	(0.119)	(0.157)	(0.087)	(0.118)	(0.162)
Dummies home team					✓		✓
Dummies visiting team						✓	✓
N	1,330	1,330	1,330	1,330	1,330	1,330	1,330
Number of clusters		25	25	550	25	25	550
Cluster home team		✓			✓		
Cluster visiting team			✓			✓	
Cluster match				✓			✓

Notes. OLS estimation of the effect of the ban on the probability of losing a game for the visiting team interacting the effect with (i) the home team being among the best five teams in the league, (ii) the visiting team being among the best five teams in the league, and (ii) both teams being among the best five teams in the league. Controls include dummies for home team in Columns (5) and (7) and dummies for visiting team in Columns (6) and (7). Beta-coefficients reported and robust standard errors in parentheses. Standard errors are clustered by home team in Columns (2) and (5), by visiting team in Columns (3) and (6), and by game interaction in Columns (4) and (7).

***Significant at 1%; **significant at 5%; *significant at 10%.

our preferred specification, column 6 of the aforementioned table. The coefficients for *Big 5* (δ_1, δ_2, and δ_3) are not statistically significant, which implies that before the ban, big and small clubs were equally likely to lose when playing away. Consistently with the result observed in Table 2, β is always significant and positive, indicating that, after the ban, small clubs are more likely to lose when playing away against other small clubs. The effect does not change if they play away against a *Big 5*; the coefficient ψ_1 is often close to 0 and never significant. When a *Big 5* plays away, the situation is different. The coefficient ψ_2 estimates the effect of the ban on losing when a *Big 5* visitor plays against a small club. It is negative and always significant, highlighting a positive differential effect of the ban for big clubs. This offsets the positive effect observed for small clubs, suggesting that the *Big 5* do not gain from the ban when playing at small clubs' stadiums.[32] Conversely, even if not always significant, the coefficient of the triple interaction (ψ_3) is positive and quantitatively important. Although the ban does not seem to affect big clubs when they play away against small clubs, it has a strong effect on them when playing at other *Big 5* stadiums, dramatically increasing their probability of losing against a direct rival.

These results suggest that moral support is relevant, and often pivotal, when there is a balance of power between the two clubs. Moral support seems to compensate for the power of monetary resources. When a *Big 5* visits a small club, the fan support is marginal. However, when a small club visits another small club, or a *Big 5* club visits another *Big 5*, without accompanying supporters, material resources are equalized, so moral support kicks in as an important nonmaterial resource. When a small club visits a *Big 5*, its resources are lower than those of the opponent. In this case, moral support also plays a role.

6. Concluding Remarks

To the best of our knowledge, this paper provides the first empirical evidence regarding the effect of moral support on performance in a natural competitive environment. Identification relies on an unusual change in Argentinean football legislation, which prohibits visiting supporters from accompanying their teams at away games. We find that without the support of their fans, visiting teams are 20% more likely to lose. This result is robust for a set of alternative specifications. In addition, we find no evidence of a change in referee decisions because of the ban, suggesting that the effect on team performance is not due to a change in referee hostility. As a counterfactual test, we run the analysis using contemporaneous cup games, where the visiting team supporters were allowed to attend. We find no effect of the ban on the cup games, which provides additional empirical support for our findings. Finally, we find that moral support is more relevant, and often pivotal, when there is a balance of power between the two teams, suggesting that moral support compensates for the power of monetary resources.

These findings are novel, and as such, they open new avenues for future research on the effect of moral support on behavior in general and on individual and team performance in particular. Moral support plays a key motivational role even in a highly competitive setting, with high monetary incentives. We expect that moral support will be even more consequential in settings with lower monetary incentives in which the degree of substitution between the two forms of compensation (monetary and moral) should be higher. The research topic is only nascent. Laboratory and field experiments can be designed to study whether the effect of moral support varies with the context, with the degree of competitiveness of the environment, with the way moral support is provided, or with who provides it. It would also be interesting to study gender differences on the effect of moral support on performance and whether the effect is different, depending on whether the subject of support is an individual or a team. Finally, it is possible to test whether the effects we find in the Argentinean football context can be replicated in other contexts by using other sources of naturally occurring exogenous shocks on moral support, such us weather conditions or transport strikes.

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Endnotes

[1] There is ample evidence of the behavioral effects of self-confidence in different domains like education, labor, and competitive sports (Stajkovic and Luthans 1998, Bandura 2000, Bandura and Locke 2003).

[2] See also Kocher et al. (2012) for a replication study.

[3] For a comprehensive review, see Carron et al. (2005), Pollard (2006), and Pettersson-Lidbom and Priks (2010).

[4] See also Dohmen and Sauermann (2016) for a survey on referee bias.

[5] For example, Cross and Uhrig (2023), using data from the five major European leagues, reported that playing without visitors and home supporters (because of COVID-19) decreased the probability that a home team wins by 5.4 percentual points. Cueva (2020), using data from 41 different professional leagues, showed that the percentage of games won by away teams went from 29% to 33% during the lockdown. Fischer and Haucap (2021) found that in the Bundesliga, the proportion of games won by home teams was reduced by

14% for closed-door games during COVID-19 lock-down. Scoppa (2021) analyzed the results of 34,852 (917 closed-door) games from nine leagues in five different countries and found that during the closed-door games (because of COVID-19) the home advantage with respect to points obtained was significantly reduced. With the presence of the crowd, home teams received 0.504 points more than visiting teams. Without crowds, they received only 0.278 points more. Finally, Reade et al. (2022) considered 160 games played without supporters in seven different European leagues since 2002 and found that home teams won 10% less than in games with fans.

[6] We replicated our analysis for the 2021 season, comparing games played with some home supporters in the stadium and games played without supporters in the stadium. Results in Online Appendix Table J.1 are not significant because of the lack of power but suggest that the probability of losing for the visiting team is lower with empty stadiums than when home supporters are in the stadium.

[7] This tragedy, known as "*Tragedia de la puerta 12*", was originated by a locked exit; the pressure caused by the mass of Boca Juniors supporters trying to exit caused the death of 71 supporters.

[8] See Online Appendix A.2 for a summary of the most salient changes that occurred after December 2014.

[9] We do not have enough information on games played before 2011.

[10] In April 2020, transfermarkt.de was the second-largest portal with a focus on football in Germany.

[11] In the first three seasons, each team played every other team twice, whereas in the 2014 season, called "*Torneo Transición*", each team played every other team once.

[12] In addition, we collected data on total shots, corners, faults, and ball possession. Unfortunately, this information is available only for less than one-third of the control group games, so we could not use these data for the analysis.

[13] The Argentinean football association (AFA) states two windows for players' transfers between teams per year, usually before the beginning of the seasons and corresponding to the end of the first half. Most of the transfers happen between two seasons. Market values are available for only half of the total number of players in the database.

[14] To collect these data, we use the website mismarcadores.es.

[15] For completeness, Online Appendix Table B.1 presents raw averages of the games that ended with a defeat for the visiting team, by season, for both League and Copa games.

[16] Note that match i means that a given team is playing at home while another given team is playing as visitor. If the same two teams play at the visitor stadium instead of the host team stadium, the match is classified as a different one. The time index t ranges from 1 to 133, because there are seven (half) seasons in our database, and in each season there are 19 turns.

[17] The number of teams is lower than the rule-of-thumb minimum number of clusters indicated by Cameron and Miller (2015); however our identification does not seem to suffer from this. When we cluster for match, we have 550 clusters. This number is lower than 25×25 because not all seasons include the same teams, implying that some teams never play with some others.

[18] In particular, we estimate the coefficients of the following model, $y_{ikt} = \alpha + \sum_{m=1\backslash 4}^{7} \beta_m D_{k=m} + \gamma_i + \varepsilon_{ikt}$, where y_{ikt} is a dummy that takes value 1 if the visiting team lost the game i that was played in the half-season k and week t; k ranges from 1 to 7 because there are seven half-seasons in our database. $D_{k=m}$ is a dummy taking value 1 if the game is played in season m. As above, α is a constant, and γ_i indicates time-invariant unobserved components related to the intrinsic characteristics of the teams or the games.

[19] The *Copa Argentina* started in 2011, although two other editions were played in 1969 and 1970.

[20] For completeness, we also estimate an event study model for the *Copa Argentina* and report estimated coefficients in the Online Appendix Figure E.1. Coefficients are never significantly different from 0; there is a not significant increase in the probability of losing for the visiting team in 2014, but this has happened more than one year since the introduction of the ban.

[21] The teams in the restricted sample are *Arsenal Sarandi*, *Atletico Rafaela*, *Belgrano*, *Boca Juniors*, *Estudiantes*, *Godoy Cruz*, *Lanus*, *Newell's*, *Racing Club*, *San Lorenzo*, and *Tigre, Velez*.

[22] A yellow card allows the player to stay in the game. With two yellow cards (or one red card), the player is immediately expelled from the game.

[23] Sutter and Kocher (2004) and Garicano et al. (2005) showed that referees can also favor home teams by adding extra time to disproportionately benefit the home team. Unfortunately, we could not find data on extra time for the Argentine League during the period of our study.

[24] The effects are even closer in terms of magnitude if we observe the real size of the effect in percentage, dividing each coefficient by the corresponding baseline level from Table 1.

[25] We consider the half season horizon to have a quite homogeneous squad, because player market sessions happen between each half-season.

[26] Note that each team plays 19 games in each half-season; therefore, we have 19 lineup pairs per team per game. Because there are two teams for each game, we end up computing 38 Jaccard's indexes per game. Given that there are 190 games in one half-season, in total we have 38*190 = 7.600 indexes per half-season.

[27] The market value is available only for selected players; we consider all players with a market value above 0, resulting in a sample of 820 players, an average of 32.8 players per team. When we observe the same player on a different team, we treat that individual as a distinct player. Online Appendix Tables K.2 and K.3 report the number of players with a market value and the average market value by sample and season. Whereas the number of reported players' values constantly increased in time, the average squad value did not change.

[28] These data are used in the literature as a proxy for team market value. Franck and Nüesch (2012), Bryson et al. (2013), and Krumer and Lechner (2018) compared Transfermarkt data with the most famous local sports magazine in Germany, *Kicker*, finding a correlation of 0.89.

[29] *Big-5* clubs are the five biggest clubs in Argentina. See Section 5 for more details.

[30] For this analysis, the sample is restricted to the 467 players that played at least one game on the starting 11.

[31] For further information on the *Big-5* clubs see also http://www.thebubble.com/who-are-argentinas-big-five-football-clubs/.

[32] The effect of the ban on losing when playing away against small teams for big teams is estimated by $\beta + \delta$, and it is not significant.

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