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All you Need is Love: The Effect of Moral Support on 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 affect 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, and often pivotal, when there is balance of 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 non-monetary resource, even in settings with high monetary incentives.

JEL: D01, D91, J24.
Keywords: Moral Support, Encouragement, Behavioral Changes, Motivation, Non-monetary Incentives, Competitive Environments

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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 in 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 & Tirole 2003). In such a model, the agent has imperfect knowledge about 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 her performance.

Despite its prevalence and importance, the evidence of the causal 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, only home team supporters could attend while the visitors stands remained empty. This provides an unusually clean oppor-

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

tunity in a real-world environment to discern the effect of moral support on behavior.

Using data from 1320 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 without their supporters increases by about 20%. 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 to different specifications, sample restrictions, time and season fixed effects. As 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 to 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 increase referee hostility towards visiting teams. After the law, referees are neither more likely to give red or yellow cards to visiting players nor 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 coaches 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 the power of monetary resources.

To the best of our knowledge, this is the first paper providing well identified empirical evidence of a causal effect of moral support 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. Previous research shows that providing children with moral and emotional support like verbal praising, company and attention from teachers, mentors or parents improves school performance (Behncke (2012); Darolia & Wydick (2011)) and prosociality (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 & 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 & Petronijevic (2018) find 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. 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 non-monetary incentives on motivation and performance (Deci (1971); Frey & Jegen (2001); Gneezy et al. (2011)). For instance, Deci (1971) shows that providing praise increases students' willingness to work on a puzzle. More recently, in a controlled field experiment with students, Bradler et al. (2016) find that unexpected public recognition by means of a thank-you card increases students' group performance. Davies & Fafchamps (2017) show 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 non-monetary incentive in a highly competitive labour environment with high monetary incentives in place.

Finally, this paper contributes to the economics literature using sport data to understand human behavior (see Palacios-Huerta (2014) for an excellent review). Apesteguia & Palacios-Huerta (2010) use data on football penalty kicks to identify the effect of psychological pressure on the probability of scoring, depending on the order of kicks.[2] Feri et al. (2013) find 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 sport 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 sport competitions both individually (e.g. Koning (2011)) and in teams (e.g. Gómez & Pollard (2011); Liardi & Carron (2011)).[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) show that social pressure biases football referees toward home teams.[4] We show that this channel does not play a role in the context of our study.

[2]See also Kocher et al. (2012) for a replication study.
[3]For a comprehensive review see Carron et al. (2005); Pettersson-Lidbom & Priks (2010) and Pollard (2006).
[4]See also Dohmen & Sauermann (2016) for a survey on referee bias.

Recently, due to 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 due to referee bias as a consequence of social pressure (Bryson et al. (2021); Cueva (2020); Scoppa (2021); Dilger & Vischer (2020); **?**; Fischer & Haucap (2020); Endrich & Gesche (2020); Cross & Uhrig (2020); Sors et al. (2020)). We believe that compared to 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 did not only affect 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. 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 of the visiting team was only for *League* games and not for *Copa Argentina* games, which we use as a counterfactual experiment.

2 Context and Data

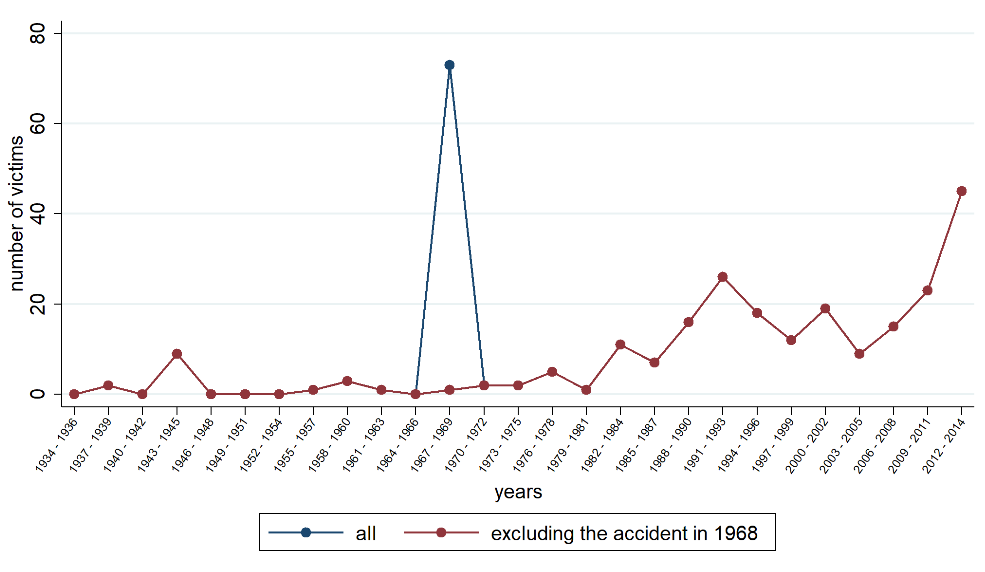
2.1 Context

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", up to date, 323 people have died due to violence episodes in Argentinean football games. Despite the implementation of different safety measures, such as increasing the number of police agents in games or installing security cameras in the stadiums, the magnitude of the problem has only worsened with time. Figure 1 shows the evolution of the number of victims in Argentinean football from 1934 to 2014. Excluding the massive tragedy of 1968 during a River Plate vs. Boca Juniors game[5], the overall trend over the past century indicates an increasing number of deaths, achieving its maximum in the triennium 2012-2014.

The 10th of June 2013 marked a turning point in the history of Argentinean football. During the first division (Primera División) game between Club Atlético Lanús and Estu-

[5]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 seventy one supporters.

Figure 1: Deaths from violence in Argentinean football



This Figure shows the number of deaths due to episodes of violence in stadiums during professional football games in Argentina. The database was constructed based on the information provided by the NGO "Salvemos el fútbol" and published by the newspaper "La Nación"

diantes 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, 20 August, 2013). Only home team supporters could enter the stadium while the visitors stand had to remain empty. In 2015, the government occasionally lifted the ban for some select games as a pilot experiment. Since the lifting of the ban was far from random, we consider the natural experiment to be in effect between June 2013 and December 2014.

This ban in Argentina provides an ideal natural experiment to test for the effect of moral support on performance. As stated by Palacios-Huerta (2014) "of the three ingredients that soccer offers, the most essential to its success is neither the ball nor the players but the flag". According to Alabarces & Rodrigues (1996), football is a major means of mass communication in the world, and one of the strongest identification practices of the popular sectors in most Latin America countries. Supporting a particular club is a form of identity, and this is particularly strong for Argentinean football supporters. Argentinean supporters do not consider themselves as spectators, but as the "twelfth player". They invent hundreds of different elaborated songs to support their teams, they jump and sing these songs during the whole game, even (or specially) when their team is losing. They move in big hordes, bringing their flags wherever the team plays, even thousands of kilometers away, as a signal of loyalty and support to the “colours they love".

2.2 Data

To assess the impact of the ban on visitor teams performance, we collected data from the Argentinean first division games played between August 2011 and December 2014.[6] Our primary source of data is the popular football website transfermarkt.com.[7] Transfermarkt contains scores, results and rankings of numerous leagues globally, as well as information on companies, players' careers and transfers. As shown by Bryson et al. (2013) and Frick & Prinz (2006), estimated players' values are extremely accurate and take into account salaries, signing fees, bonuses, and transfer fees (Franck & Nüesch 2012).

Our main dataset 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.[8] 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.[9] We observe team lineup at each game including information on all the players that were on the game roster. Further, we retrieve information on the entire squad value at the beginning of each season.[10]

In addition, we also scraped data on the national cup (*Copa Argentina*) games that were played in the same period of the study.[11] The ban did not apply to the *Copa Argentina* games, which makes these games an informative counterfactual group. However, this additional dataset contains only 161 games and the teams are often not the same as those

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

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

[8] 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.

[9] 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.

[10] 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 happens between two seasons. Market values are available for only half of the total number of players in the database.

[11] To collect these data we use the website *mismarcadores.es*.

playing in the main league. This limitation makes the sample not suitable for a robust difference in difference specification. Therefore, we only use these data as a robustness check. For the *Copa Argentina* games we are able to record only the final results.

Table 1: Summary Statistics

	Before		After	
	Mean	SD	Mean	SD
Visiting team losing (share)	0.403	0.491	0.462	0.499
Score difference (T1-T2)	0.270	1.459	0.393	1.524
Goals scored by Home Team	1.232	1.117	1.337	1.146
Goals scored by Visiting Team	0.962	0.986	0.944	1.005
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	0.067	0.239	0.080	0.271
Number of games	739		591	

This table reports the summary statistics of the dataset we use for the main analysis. Columns (1) and (3) report the average values before and after the ban, respectively, and Columns (2) and (4) report the standard deviations. “Visiting team losing (share)" refers to the proportion of games ended with a victory for the home team. “T1-T2" refers to the difference between the goals scored by the home team (T1) and the goals scored by the visiting team (T2).

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 dataset. Notice that visiting teams are more likely to loose 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 loosing of a visiting team is higher after the ban. The score differences in favor of home teams also increases, 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 does not change with the ban. If anything, and at odds with what the literature on referee bias would predict, the number of red and yellow cards given to visitors decreases. The next section provides a formal econometric analysis for these observations.

3 Impact Estimates

3.1 Empirical Strategy

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 winning, 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 as follows:

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

Where y_{it} is a dummy which takes value 1 if the visiting team won the game 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.[12] 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) game 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 game level.[13]

Our empirical strategy 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 non existence of other forces that could affect

[12] Note that game 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 game is classified as a different one. The time index t ranges from 1 to 133, since there are 7 (half) seasons in our database and in each seasons there are 19 turns.

[13] The number of teams is lower than the rule of thumb minimum number of clusters indicated by Cameron & Miller (2015), however our identification does not seem to suffer from this. When we cluster for games, we have 550 clusters. This number is lower than 25x25 because not all seasons include the same teams, implying that some teams never play with some others.

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 would have never been implemented.

In addition to including season and round fixed effects to control for heterogeneity within a season and round, in Sections 3.3 and 3.4 we perform two additional analyses to sharpen our identification strategy. 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 perfectly as a counterfactual experiment since the ban for visiting team supporters does not apply to the cup, 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 the four seasons.

3.2 Main Result: Effect on Team Performance

Table 2 reports the coefficients of estimating eq. (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) reports OLS estimates of eq. (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.[14] Our preferred specification is reported in Column (6), where we control for visiting team fixed effects, because all the unobservable time invariant components related only to the visiting team are taking 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).

For completeness, 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 eq. (1). As dependent variable

[14]Table A1 shows that these results are robust to using a Logit model.

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	1330	1330	1330	1330	1330	1330	1330	1330
Number of Clusters		25	25	550	25	25	550	550
Cluster Home Team		✓			✓			
Cluster Visiting Team			✓			✓		
Cluster Match				✓			✓	✓

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%.

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 visiting team level. As it 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.

In the Appendix (Table A2) 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 - col. 6), but does not affect the number of goals scored by visiting teams (Panel B - col. 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 such an ideal setting. We exploit the fact that the AFA did not implement the ban for games played in the

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)
Presence of the Ban	1.184*	1.184*	1.184*	1.184*	1.165	1.302**	1.292**
	(0.117)	(0.114)	(0.115)	(0.117)	(0.114)	(0.136)	(0.154)
N	1330	1330	1330	1330	1330	1330	1330
Number of Clusters		25	25	550	25	25	550
Cluster Home Team		✓			✓		
Cluster Visiting Team			✓			✓	
Cluster Match				✓			✓

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 to 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), (7). *** significant at 1%, ** significant at 5%, * significant at 10%.

contemporaneous tournament, *Copa Argentina*.[15] This constitutes the perfect counterfactual, as these are games played in the same time period as those of the League, by the same 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 eq. (1) using games played for the *Copa Argentina* instead of games played in the League. Table A3 presents the results. The coefficient of the OLS estimation for the usual specification, reported in Column (6) is not statistically significant. This provides additional empirical support to the identification of the main result put forward in this paper, that it was the ban and not other potential factors contemporaneous to the ban that negatively affected visiting teams performance.

3.4 Excluding Promoted and Relegated Teams

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

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

division while 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 Table A4, our main results remain robust to this restriction.

As an extra 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 twelve teams that participated in all the seasons.[16] Again, as Table A5 shows, our results are robust to this sample restriction.

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, coach 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 towards them. There is evidence showing that referees can bias their decisions due to supporters pressure (Sutter & Kocher (2004); Garicano et al. (2005)). The lack of visiting supporters might alleviate that pressure and increase referee hostility towards 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[17] to players in an unfair way Boyko et al. (2007).[18] We test whether the ban increased the hostility of referees towards visiting teams by estimating eq. (1) using as out-

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

[17] 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.

[18] Garicano et al. (2005) show that referees can also favour 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.

come 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 A6 on yellow cards, Table A7 on red cards, and Table A8 on penalties. Panels A of the tables present results on the cards and penalties inflicted to *home* teams while Panels B focus on cards and penalties to *visiting* teams. Overall, we observe no significant effect of the ban on red cards or penalties awarded to visiting or home teams. We observe a reduction of yellow cards given to both teams. However, coefficients are not significantly different from zero in most specifications. Moreover, the sign of the effect is the oppositive to what we would expect if referee hostility increased towards visiting teams. Hence, we conclude that there is evidence that the lack of visiting supporters does not increase referee bias against visiting teams, which implies 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 Coaches?

Another potential confounding factor that could be affected by the presence of the ban regards the strategy of coaches. In principle, coaches could internalize that without the support when playing away they would be more likely to loose and adapt their strategy accordingly. In addition, since the ban does not apply to non-league games, coaches 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 our identification strategy.

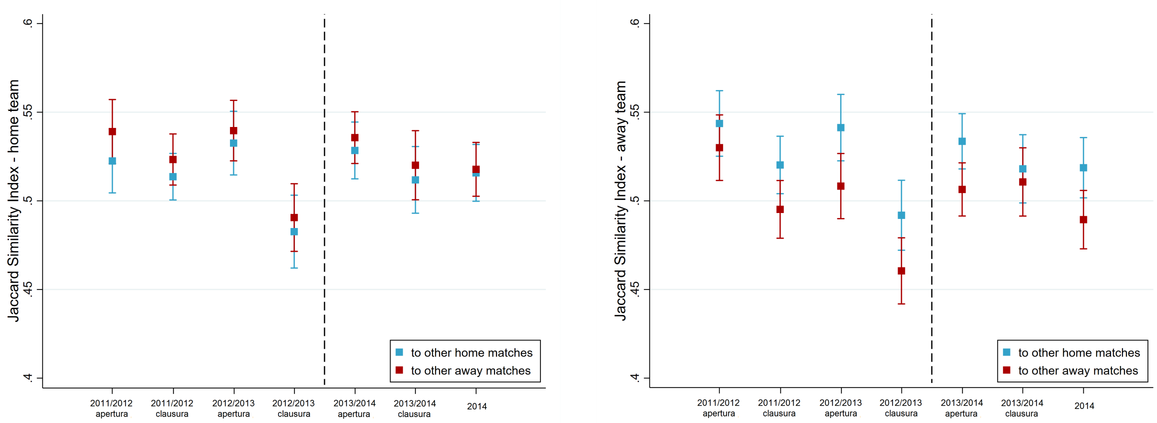
In order to test this potential mechanism, we perform two set of analyses. First, we include different sets of time controls. We estimate our main specification with half-season fixed effects (apertura/clausura) and turn/week fixed effects (from 1 to 19). In this way every single turn/week within a season is compared to the correspondent turn/week in other seasons. We also estimate eq. (1) adding month fixed effects (from 1 to 12) to compare all games played in a particular month of the year. Tables A9 and A10 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 while it increases by 1 percent in the second model. These results rule out any potential change of visiting teams performance that could happen due to time, other than the ban.

Second, we directly test for potential changes in lineups between home and visiting games after the ban. For this purpose, we calculate the degree of similarity between the team lineups within each half season and check whether there are significant changes after the ban.[19] More specifically, for a given team, we consider the 11 starting players of each game and compare this set with all the other lineups of the same team for the same half season in pair. For each lineup pair we compute the Jaccard similarity index (Jaccard 1908). The Jaccard similarity index measures the similarity between different sample sets and is defined as the quotient of the intersection between two sets divided by their union: the greater the index, the greater the similarity between the two sets. At the end of this procedure we have 38 indexes per game, indicating how close the lineup of each team playing that game is to the other lineups of the same team in the half season. Since for each game we have a home and a visiting team, we can divide all our Jaccard indexes into four groups: similarity between (i) home lineups to all the other home lineups, (ii) home to visiting, (iii) visiting to home and (iv) visiting to visiting.

Figure 2: Jaccard Similarity Index

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 1309 games for which Transfermarkt reports exactly eleven starting players for each team.

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 visiting 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 visiting,

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

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 coaches 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 eq. 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. Table A11 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 1309 games as the starting lineup of 11 players was not available for 21 games. As expected, our main result is robust to 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 Table A11, we conclude that coaches 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?

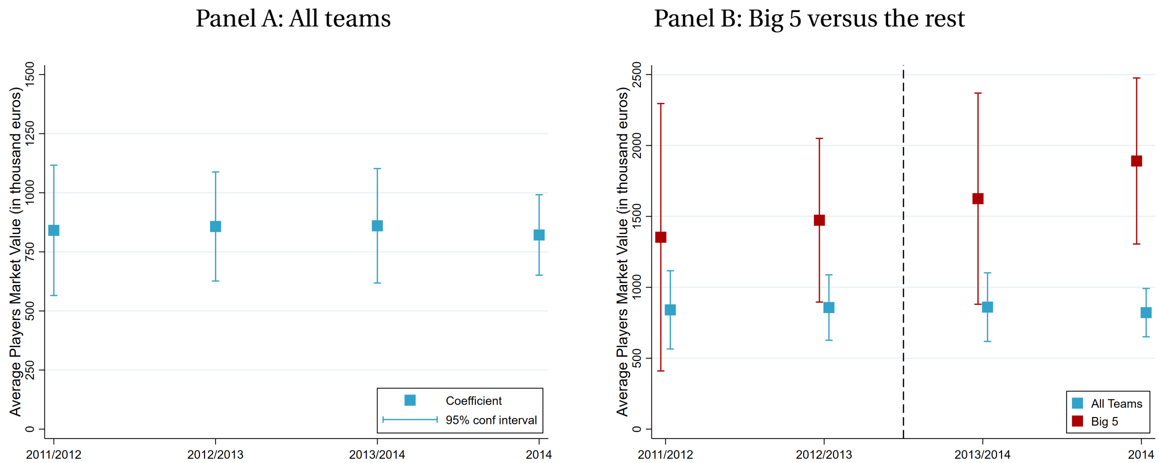
The presence of the ban could potentially affect the market value of teams. For instance, teams may be motivated to sell some of their top players to foreign leagues as a way to compensate for the reduction in the seasonal income due to the lack of visiting supporters at the stadium. This would imply an average decrease in the market value of teams between the end of 2012/13 season and the beginning of 2013/14 season with potential consequences on team performance. To test for this potential channel, we analyze player monetary value using data from Transfermarkt.[20] 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.[21]

Figure 3 shows the evolution of the average player market value by season. In the top panel we represent the average value of all teams playing in the first division while in the bottom panel we separate the analysis between the *Big-5* clubs, reported in red and all the

[20]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 in a different team we treat that individual as a distinct player.

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

Figure 3: Average Player Values by Season



This Figure shows the average value of all players playing in the First Argentinean League by season. Note: The sample includes all the 820 players reported in the Transfermarkt database with a player value greater than 0.

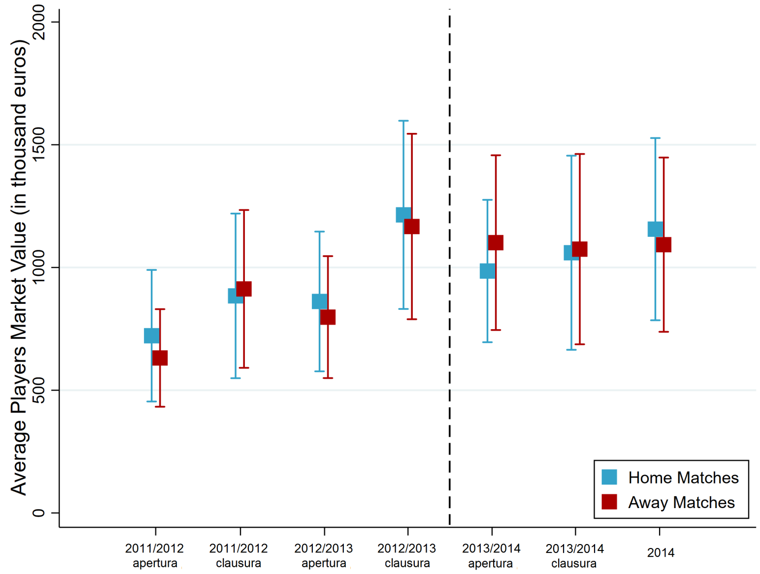
teams together, reported in blue.[22] We separate the analysis because, if there is an effect on market value, we believe that it should be more salient for bigger teams, which have more top-value players. In the top panel, we observe that the average value of players does not change substantially between seasons when considering all the teams in the analysis, ruling out any possibility of *fire-sell* due to the loss of income after the ban. In the bottom panel, not surprisingly, we observe that the average market value for the *Big-5* is, for each season, much higher compared to 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 coach chooses. Following the same argument in Section 4.2, coaches 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.[23] Figure 4 reports the average player market value for the 7 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.

[22] *Big-5* clubs are the five biggest clubs in Argentina. See Section 4.4 for more details.

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

Figure 4: Average Player Values by Half-Season



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

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 Table A12, in all 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. Since, 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.

4.4 Heterogeneous Treatment Effect

In this subsection, we analyse whether the lack of moral support is more consequential for bigger or smaller clubs. A priori, it is not clear what to expect. While 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, instead, may 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, the highest number of followers in social media. They manage the biggest budgets and have won the most national and international cups (*AFA| FIFA - Informe Clubes Fútbol* 2019).[24] 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 eq. (1) by binary variables for home and visiting team being a *Big 5* and interactions with the ban indicator.

$$\begin{aligned} y_{it} &= \alpha + \beta L_{it} + \delta_1 B5H_i + \delta_2 B5V_i + \delta_3 B5H_i \times B5V_i \\ &\quad + \psi_1 L_{it} \times B5H_i + \psi_2 L_{it} \times B5V_i + \psi_3 L_{it} \times B5H_i \times B5V_i + \gamma_i + \varepsilon_{it} \end{aligned} \tag{2}$$

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 eq. (1). $B5H_i$ and $B5V_i$ are binary variables for home (H) and visiting (V) team being a *Big 5*.

Table 4 reports results of this analysis. The coefficients for *Big 5* (δ_1, δ_2 and δ_3) are never significant, which implies that before the ban, big and small clubs are 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 situations is different. The coefficient ψ_2 estimates the effect of the ban when a *Big 5* visitor loses to 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* clubs do not gain from the ban when playing at small clubs' stadiums.[25] Conversely, even if not always significant, the coefficient of the

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

[25] The effect of the ban on losing when playing away against small teams for big teams is estimated by $\beta + \delta$,

Table 4: Heterogeneous Effects: The *Big-5*

OLS Estimation							
Dependent Variable: *=1 if Visiting team loses*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
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	1330	1330	1330	1330	1330	1330	1330
Number of Clusters		25	25	550	25	25	550
Cluster Home Team		✓			✓		
Cluster Visiting Team			✓			✓	
Cluster Match				✓			✓

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), (7). *** significant at 1%, ** significant at 5%, * significant at 10%.

triple interaction (ψ_3) is positive and quantitatively important. While 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* clubs' stadiums, dramatically reducing their probability of winning 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 the power of monetary resources. When a *Big 5* club 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 non-material resource. When a small club visits a *Big 5*, its re-

and it is not significant.

sources are lower than those of the opponent. In this case moral support also plays a role.

5 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. Our identification strategy takes advantage of an unusual change in Argentinean football legislation, which prohibits visiting supporters from accompanying their teams on away games. We find that, without the support of their fans, visiting teams are 20% more likely to lose. This result is robust to a set of alternative specifications. In addition, we find no evidence of a change in referee decisions due to 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 to 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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Appendix

Table A1: Logit Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Maximum Likelihood Estimation								
Dependent Variable: *Dummy for losing/not losing a match for the visiting team*								
Presence of the Ban (d)	0.059**	0.059**	0.059**	0.059**	0.027*	0.093***	0.056*	0.111**
	(0.027)	(0.026)	(0.029)	(0.027)	(0.015)	(0.031)	(0.029)	(0.045)
Dummies Home Team					✓		✓	
Dummies Visiting Team						✓	✓	
Dummies Match								✓
N	1330	1330	1330	1330	1330	1330	1330	856
Number of Clusters		25	25	550	25	25	550	295
Cluster Home Team		✓			✓			
Cluster Visiting Team			✓			✓		
Cluster Match				✓			✓	✓

Maximum likelihood estimation of a logit model 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%.

Table A2: Effect of the ban on Goals Scored

	Maximum Likelihood Estimation						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<u>Panel A</u>							
Dependent Variable: *Number of goals scored by the local team*							
Presence of the Ban	1.176	1.176*	1.176	1.176*	1.136	1.291**	1.257*
	(0.117)	(0.106)	(0.142)	(0.114)	(0.108)	(0.166)	(0.148)
<u>Panel B</u>							
Dependent Variable: *Number of goals scored by the visiting team*							
Presence of the Ban	0.947	0.947	0.947	0.947	0.948	0.899	0.897
	(0.0964)	(0.100)	(0.106)	(0.0948)	(0.112)	(0.123)	(0.112)
<u>Controls</u>							
Dummies Home Team					✓		✓
Dummies Visiting Team						✓	✓
N	1330	1330	1330	1330	1330	1330	1330
Number of Clusters		25	25	550	25	25	550
Cluster Home Team		✓			✓		
Cluster Visiting Team			✓			✓	
Cluster Match				✓			✓

]Panel A: Maximum Likelihood estimation of an ordered Logit Model of the effect of the ban on the number of goals scored by the home team. Panel B:Maximum Likelihood Estimation of an ordered Logit Model of the effect of the ban on the number of goals scored by the visiting 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), (7). *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A3: Counterfactual Test: Main Regression Specifications with Cup Games

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OLS Estimation							
Dependent Variable: *=1 if Visiting team loses*							
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				✓			✓

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), (7). *** significant at 1%, ** significant at 5%, * significant at 10%.

Table A4: Main Regression Specifications Excluding Promoted and Relegated Teams just after the Ban

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	0.058*	0.058*	0.058*	0.058*	0.053*	0.069*	0.064*	0.071*
	(0.033)	(0.028)	(0.033)	(0.032)	(0.026)	(0.033)	(0.034)	(0.042)
Dummies Home Team					✓		✓	
Dummies Visiting Team						✓	✓	
Dummies Match								✓
N	904	904	904	904	904	904	904	904
Number of Clusters		19	19	315	19	19	315	315
Cluster Home Team		✓			✓			
Cluster Visiting Team			✓			✓		
Cluster Match				✓			✓	✓

OLS estimation of the effect of the ban on the probability of losing a game for the visiting team. Sample: all games but the ones played by the teams that got promoted or relegated in 2013, i.e. *Independiente, Union Santa Fe, San Martin de Tucumán, Olimpo de Bahía Blanca, GELP and Rosario Central.* 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%.

Table A5: Main Regression Specifications Excluding all Promoted and Relegated Teams during the Time-span of the Study

	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	0.079*	0.079**	0.079*	0.079*	0.080**	0.083*	0.084*	0.093*
	(0.046)	(0.034)	(0.040)	(0.046)	(0.034)	(0.041)	(0.046)	(0.054)
Dummies Home Team					✓		✓	
Dummies Visiting Team						✓	✓	
Dummies Match								✓
N	462	462	462	462	462	462	462	462
Number of Clusters		12	12	132	12	12	132	132
Cluster Home Team		✓			✓			
Cluster Visiting Team			✓			✓		
Cluster Match				✓			✓	✓

OLS estimation of the effect of the ban on the probability of losing a game for the visiting team. Sample: all games but the ones played by the teams that got promoted or relegated during the whole analyzed period. 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%.

Table A6: Effect of the ban on Yellow Cards

	OLS Estimation							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<u>Panel A</u>								
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)
<u>Panel B</u>								
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)
<u>Controls</u>								
Dummies Home Team					✓		✓	
Dummies Visiting Team						✓	✓	
Dummies Match								✓
N	1328	1328	1328	1328	1328	1328	1328	1328
Number of Clusters		25	25	550	25	25	550	550
Cluster Home Team		✓			✓			
Cluster Visiting Team			✓			✓		
Cluster Match				✓			✓	✓

Panel A: OLS estimation of the effect of the ban on the number of yellow cards shown to home team players. Panel B: OLS estimation of the effect of the ban on the number of yellow cards shown to visiting team players. 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%.

Table A7: Effect of the ban on Red Cards

	OLS Estimation							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A								
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)
Panel B								
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)
Controls								
Dummies Home Team					✓		✓	
Dummies Visiting Team						✓	✓	
Dummies Match								✓
N	1328	1328	1328	1328	1328	1328	1328	1328
Number of Clusters		25	25	550	25	25	550	550
Cluster Home Team		✓			✓			
Cluster Visiting Team			✓			✓		
Cluster Match				✓			✓	✓

Panel A: OLS estimation of the effect of the ban on the number of red cards shown to home team players. Panel B: OLS estimation of the effect of the ban on the number of red cards shown to visiting team players. 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%.

Table A8: Effect of the ban on penalties awarded

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A								
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)
Panel B								
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	1328	1328	1328	1328	1328	1328	1328	1328
Number of Clusters		25	25	550	25	25	550	550
Cluster Home Team		✓			✓			
Cluster Visiting Team			✓			✓		
Cluster Match				✓			✓	✓

Panel A: OLS estimation of the effect of the ban on the probability of having a penalty awarded to the home team.Panel B: OLS estimation of the effect of the ban on the probability of having a penalty awarded to 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%.

Table A9: Time Controls: Main Regression Specifications with Half-season and Round Dummies

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	0.060**	0.060**	0.060*	0.060**	0.046*	0.088**	0.075**	0.075*
	(0.028)	(0.027)	(0.032)	(0.027)	(0.024)	(0.032)	(0.031)	(0.042)
Dummies Home Team					✓		✓	
Dummies Visiting Team						✓	✓	
Dummies Match								✓
Dummy Half-Season	✓	✓	✓	✓	✓	✓	✓	✓
Dummies Week/Round	✓	✓	✓	✓	✓	✓	✓	✓
N	1330	1330	1330	1330	1330	1330	1330	1330
Number of Clusters		25	25	550	25	25	550	550
Cluster Home Team		✓			✓			
Cluster Visiting Team			✓			✓		
Cluster Match				✓			✓	✓

OLS estimation of the effect of the ban on the probability of losing a game for the visiting team controlling for dummy for half-season(Apertura/Clausura), and round dummies (from 1 to 19). Further 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%.

Table A10: Time Controls: Main Regression Specifications with month dummies

	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	0.068**	0.068**	0.068**	0.068**	0.054**	0.096***	0.083***	0.096**
	(0.028)	(0.026)	(0.030)	(0.027)	(0.024)	(0.030)	(0.031)	(0.041)
Dummies Home Team					✓		✓	
Dummies Visiting Team						✓	✓	
Dummies Match								✓
Dummies Month	✓	✓	✓	✓	✓	✓	✓	✓
N	1330	1330	1330	1330	1330	1330	1330	1330
Number of Clusters		25	25	550	25	25	550	550
Cluster Home Team		✓			✓			
Cluster Visiting Team			✓			✓		
Cluster Match				✓			✓	✓

OLS estimation of the effect of the ban on the probability of losing a game for the visiting team controlling for month dummies. Further 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%.

Table A11: Main Regression Specifications Controlling for Lineups

	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	0.056**	0.056**	0.056*	0.056**	0.050**	0.081***	0.076**	0.079*
	(0.027)	(0.021)	(0.027)	(0.026)	(0.020)	(0.028)	(0.030)	(0.041)
Jaccard Home to Home	0.006**	0.006**	0.006**	0.006**	0.006**	0.006**	0.006**	0.006
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)
Jaccard Home to Visiting	-0.001	-0.001	-0.001	-0.001	0.001	-0.001	0.001	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.005)
Jaccard Visiting to Home	-0.000	-0.000	-0.000	-0.000	-0.000	-0.001	-0.001	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Jaccard Visiting to Visiting	-0.005*	-0.005*	-0.005	-0.005*	-0.005*	-0.006*	-0.006**	-0.009**
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Dummies Home Team					✓		✓	
Dummies Visiting Team						✓	✓	
Dummies Match								✓
N	1309	1309	1309	1309	1309	1309	1309	1309
Number of Clusters		25	25	550	25	25	550	550
Cluster Home Team		✓			✓			
Cluster Visiting Team			✓			✓		
Cluster Match				✓			✓	✓

OLS estimation of the effect of the ban on the probability of losing a game for the visiting team. Jaccard home(visiting) to home[visiting] refers to the similarity index between the lineup of the home(visiting) team to the other lineups of the same team in its home[visiting] games. The number of observations corresponds to the number of games with exactly 11 starting players per 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%.

Table A12: 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^{**}	0.048^{*}	0.086^{***}	0.075^{**}	0.080^{*}
	(0.027)	(0.027)	(0.030)	(0.027)	(0.024)	(0.029)	(0.031)	(0.041)
Market Value Home Team	0.050^{**}	0.050^{**}	0.050^{**}	0.050^{**}	0.000	0.050^{**}	0.003	-0.003
	(0.020)	(0.020)	(0.019)	(0.020)	(0.015)	(0.019)	(0.030)	(0.041)
Market Value Visiting Team	-0.067^{***}	-0.067^{***}	-0.067^{***}	-0.067^{***}	-0.068^{***}	-0.010	-0.012	-0.017
	(0.019)	(0.019)	(0.022)	(0.019)	(0.019)	(0.022)	(0.028)	(0.037)
Dummies Home Team					✓		✓	
Dummies Visiting Team						✓	✓	
Dummies Match								✓
N	1330	1330	1330	1330	1330	1330	1330	1330
Number of Clusters		25	25	550	25	25	550	550
Cluster Home Team		✓			✓			
Cluster Visiting Team			✓			✓		
Cluster Match				✓			✓	✓

OLS estimation of the effect of the ban on the probability of losing a game for the visiting team. Market Value refers to the average value of a single player in million euros. 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%.