The Impact of Previous Losses on Match Attendance: Which Teams' Fans Turn Away?

Introduction

As football continues to grow into a global phenomenon, it draws in a rapidly expanding and increasingly diverse fan base. This raises fundamental questions about fan behavior: why do people support certain teams, and what factors influence their loyalty? While traditional explanations often emphasized family ties and local affiliations, contemporary football fandom is increasingly shaped by team performance and success.

This study investigates how match outcomes, specifically losses, influence fan attendance in the Czech football league. The goal is to identify which clubs have loyal supporters and which rely more heavily on recent success to fill the stands.

Data description

The analysis is based on match-level data from the Czech Football Chance Liga for the 2024/2025 season. The dataset was obtained from the publicly accessible website https://www.livesport.cz. It includes a total of 258 matches, covering the regular season (30 rounds) and subsequent playoff rounds. The league structure features three postseason groups based on final standings: a championship group, a mid-table group, and a relegation group. After the playoffs, the team finishing last is automatically relegated, while the 14th and 15th teams compete in a play-off with the 2nd and 3rd teams from the Czech National League.

The cleaned dataset includes the following variables:

Attendance_percentage

Type: float

The percentage of the stadium's total capacity occupied during the match. Serves as a proxy for match-day attendance intensity. Ranges from 0% to 100%.

previous_loss

Type: binary (0/1)

Equals 1 if the home team lost its previous match, and 0 otherwise. Captures short-term performance effects on attendance.

is_derby

Type: binary (0/1)

Indicates whether the match is a local derby (1 = yes, 0 = no). Derbies generally attract more fans due to regional rivalries.

vs_big_team

Type: binary (0/1)

Equals 1 if the away opponent is a traditionally popular or strong team. These matches tend to generate greater spectator interest.

• is_weekend

Type: binary (0/1)

Indicates whether the match was played on a weekend. Weekend fixtures typically allow for higher attendance due to scheduling convenience.

• weather_code_coco

Type: categorical (integer)

A numerical code representing weather conditions at kickoff (e.g., sunny, cloudy, rainy). Weather can impact attendance decisions.

• temperature_at_kickoff

Type: float (°C)

Temperature at the start of the match in degrees Celsius. Extreme conditions may discourage or encourage attendance.

• home_team

Type: categorical (string)

The name of the home team playing the match.

Methodology & Results

To investigate the determinants of match attendance in the Czech Football League, we estimate a linear panel data model using Fixed Effects (FE) estimation. Since attendance patterns may vary substantially between clubs (due to fan base size, stadium capacity, etc.), a team fixed-effects approach is appropriate to isolate within-team variation.

We estimate the following model using the PanelOLS estimator with clustered standard errors at the team level:

 $\begin{aligned} &\textbf{attendance_percentage}_{i_t} = \alpha_i + \beta 1 * previous_loss_{i_t} + \beta 2 * is_derby_{i_t} + \beta 3 * \\ &vs_big_team_{i_t} + \beta 4 * is_weekend_{i_t} + \beta 5 * weather_code_coco_{i_t} + \beta 6 * \\ &temperature_at_kickoff_{i_t} + \varepsilon_{i_t} \end{aligned}$

Where:

• *i* indexes teams and *t* indexes matches,

- α_i represents team fixed effects,
- Standard errors are clustered by team to account for intra-team autocorrelation

On **Table 1**. We can see the estimated coefficient for previous_loss is -4.64 and statistically significant at the 1% level (p = 0.0006). This implies that, on average, a team that lost its previous match experiences a decrease in attendance by approximately 4.64 percentage points in their next home game, holding other factors constant and within the same team. This result suggests that fans are sensitive to recent team performance and are less likely to attend after a poor result.

Table 1: Panel OLS

Panel Regression Results	
Depe	endent variable: attendance_percentage
	Model
	(1)
const	45.448***
	(5.014)
previous_loss	-4.640 ^{***}
	(1.691)
is_derby	10.531
	(9.813)
vs_big_team	40.135***
	(4.522)
is_weekend	2.943
	(4.578)
weather_code_coco	0.109
	(0.292)
temperature_at_kickoff	0.458***
	(0.127)
R-squared (within)	0.511
F-statistic	40.75
P-value	0.0000
Observations	258
N. of groups	18
R^2	0.511
Residual Std. Error	15.250 (df=234)
F Statistic	40.752*** (df=24; 234)
Note:	*p<0.1; **p<0.05; ***p<0.01

The F-test for poolability rejects the null hypothesis that all teams share a common intercept (p-value < 0.001), supporting the use of fixed effects. The overall within R^2 is 0.511, indicating that approximately 51% of the within-team variation in attendance is explained by the model.

Which Teams' Fans Turn Away?

We observe that, within the Czech football league, a previous loss has a statistically significant negative impact on match attendance. To further explore heterogeneity in this effect, we estimate OLS regressions separately for each of the 16 teams. This allows us to assess whether some teams are more affected by recent losses than others, and to identify where the so-called "success fans" behavior is most prevalent. For detailed regression outputs, see the **Appendix**.

For instance, teams like Mladá Boleslav and Slovan Liberec, show large attendance drops after a loss (-11.8 p.p and -17.5 p.p), though not statistically significant. Baník Ostrava also sees a decline of -9.3 p.p. These may reflect more result-dependent fans.

On the other hand, Karviná shows an increase of 15.8 p.p and Viktoria Plzeň even 20.6 p.p after a loss. This suggests stronger loyalty among their supporters.

If we focus on the effect of temperature on attendance, we can see that Viktoria Plzeň shows the strongest and statistically significant positive relationship, with warmer weather increasing attendance by about 2.1 p.p. Mladá Boleslav and Jablonec also show significant positive effects, though smaller. In contrast, Slovácko and Slovan Liberec show negative, but insignificant results.

Bootstrap

The limitation of the initial results lies in small sample size. To address this, we applied bootstrapping with 750 bootstrap samples, which is a resampling technique that repeatedly draws samples with replacement from the original data to estimate the distribution of the coefficient. This approach helps improve the robustness of our estimates.

Table 2: Bootstrap

Tuble 21 Bootsti	P			
Team	Bootstrap Coef.	CI Lower (95%)	CI Upper (95%)	N
Sparta Praha	10.28	-0.43	20.14	51
Karviná	8.89	-3.67	20.98	51
Teplice	6.80	-5.04	18.78	42
Č. Budějovice	3.49	-8.16	16.25	50
Mladá Boleslav	2.42	-9.01	12.32	47
Pardubice	0.58	-10.69	12.03	47
Bohemians	0.55	-10.70	11.91	42
Zlín	0.50	-11.88	11.73	53
Slavia Praha	0.27	-14.87	15.55	38
Sigma Olomouc	-1.23	-15.75	12.50	47
Baník Ostrava	-2.64	-13.06	8.21	55
Hradec Králové	-3.46	-15.86	8.73	44
Slovácko	-3.77	-19.49	11.42	43
Jablonec	-5.16	-19.06	7.45	33
Slovan Liberec	-6.46	-18.57	4.76	51
Viktoria Plzeň	-16.21	-26.56	-4.79	56

The results of the bootstrap procedure are presented in **Table 2**. We observe that Viktoria Plzeň stands out with a statistically significant and large negative effect: attendance drops by -16.2 pp., with the entire confidence interval lying below zero. This suggests a strong presence of "success-dependent" fans. Compared to the previous result, we can observe drastically different values, suggesting that the sample contains outliers. Other teams such as Slovan Liberec, Jablonec, and Slovácko also show sizable negative coefficients, though not statistically significant. On the other hand, Sparta Praha, Karviná, and Teplice exhibit positive coefficients, suggesting that attendance may even increase slightly after a loss, but these effects are not statistically significant.

Conclusion

In summary, this study finds that the most statistically significant factor affecting match attendance is whether the home team plays against a well-known and successful opponent, particularly Slavia Praha, Sparta Praha, or Viktoria Plzeň. Additionally, both temperature and recent performance, meaning whether the team lost its previous match, show a significant effect on fan turnout.

At the individual team level, bootstrap analysis reveals that Viktoria Plzeň appears to have the success fun effect, with attendance significantly dropping after a loss. This effect is statistically significant, as the ninety-five percent confidence interval excludes zero. However, it is important to note that the confidence interval is relatively wide, indicating substantial variability and uncertainty in the estimate.

Appendix

Regression	Results:	Teams	1–4
------------	----------	-------	-----

	Dependent variable: attendance_percentage			
	Baník Ostrava	Bohemians	Dukla Praha	Hradec Králové
	(1)	(2)	(3)	(4)
Intercept	56.674***	85.831***	16.521	67.924***
	(12.832)	(23.621)	(13.639)	(7.424)
previous_loss	-9.337	-8.468	-1.851	-5.994
	(8.729)	(14.076)	(11.159)	(4.968)
temperature_at_kickoff	0.094	0.532	1.656**	-0.159
	(0.472)	(1.003)	(0.729)	(0.175)
vs_big_team	33.781***	3.304	75.132***	33.776***
	(9.376)	(20.846)	(10.228)	(3.875)
weather_code_coco	1.859	-2.288	-1.934	0.010
	(3.185)	(6.990)	(2.472)	(2.028)
Observations	17	15	16	15
\mathbb{R}^2	0.598	0.346	0.761	0.896
Adjusted R ²	0.464	0.084	0.674	0.855
Residual Std. Error	14.163 (df=12)	15.565 (df=10)	15.788 (df=11)	5.231 (df=10)
F Statistic	4.861** (df=4; 12)	0.381 (df=4; 10)	23.775*** (df=4; 11)	37.409*** (df=4; 10)
Note:			*p<0.1;	**p<0.05; ***p<0.01

Regression	Results: Teams	5_8
Regression	Results, Teallis	\mathcal{I}

	Dependent variable: attendance_percentage				
	Jablonec	Karviná	Mladá Boleslav	Pardubice	
	(1)	(2)	(3)	(4)	
Intercept	37.451***	33.787***	37.626***	42.438***	
	(10.157)	(10.138)	(9.184)	(11.341)	
previous_loss	-3.892	15.779	-11.750	1.970	
	(5.587)	(19.941)	(7.536)	(11.340)	
temperature_at_kickoff	0.737**	1.116	0.965**	0.265	
	(0.310)	(0.719)	(0.414)	(0.619)	
vs_big_team	46.462***	47.651***	50.966***	50.182***	
	(8.892)	(8.419)	(10.841)	(8.326)	
weather_code_coco	-0.927	-1.493	-1.940	1.653	
	(2.131)	(1.027)	(1.871)	(1.464)	
Observations	16	15	17	16	
R^2	0.910	0.696	0.768	0.524	
Adjusted R ²	0.878	0.575	0.691	0.351	
Residual Std. Error	7.729 (df=11)	14.019 (df=10)	13.894 (df=12)	18.936 (df=11)	
F Statistic	9.920*** (df=4; 11)	249.502*** (df=4; 10)	16.152*** (df=4; 12)	16.805*** (df=4; 1	

Note: *p<0.1; **p<0.05; ***p<0.01

Regression Results: Teams 9–	12

	Dependent variable: attendance_percentage			
	Sigma Olomouc	Slavia Praha	Slovan Liberec	Slovácko
	(1)	(2)	(3)	(4)
Intercept	26.147***	92.257***	37.127**	58.049
	(6.471)	(6.389)	(17.010)	(37.493)
previous_loss	-5.434		-17.519	-12.823
	(7.604)		(12.007)	(13.586)
temperature_at_kickoff	1.260	0.040	-0.143	-0.631
	(0.993)	(0.176)	(0.984)	(0.781)
vs_big_team	65.916***	5.602***	44.283***	45.302***
	(6.197)	(2.101)	(16.728)	(12.215)
weather_code_coco	-1.180	0.226	0.586	1.178
	(1.646)	(1.441)	(1.344)	(11.174)
Observations	16	17	15	16
\mathbb{R}^2	0.781	0.239	0.549	0.573
Adjusted R ²	0.701	0.064	0.369	0.417
Residual Std. Error	14.936 (df=11)	3.740 (df=13)	20.366 (df=10)	17.675 (df=11)
F Statistic	52.558*** (df=4; 11)	2.698* (df=3; 13)	5.446** (df=4; 10)	5.969*** (df=4; 1
Note:			*p<0.1: *	*p<0.05; ***p<0.0

Regression Results: Teams 13–16

	Dependent variable: attendance_percentage			
	Sparta Praha (1)	Teplice (2)	Viktoria Plzeň (3)	České Budějovice (4)
Intercept	76.947***	17.233***	20.922	14.326
	(6.381)	(5.734)	(20.255)	(9.541)
previous_loss	1.606	1.547	20.637**	5.887
	(4.811)	(3.918)	(9.434)	(12.316)
temperature_at_kickoff	0.440**	0.452	2.053***	0.848
	(0.222)	(0.303)	(0.732)	(0.575)
vs_big_team		63.982**	33.161***	70.100***
		(28.618)	(8.323)	(15.126)
weather_code_coco	0.674	-1.451	9.097**	1.109^{*}
	(0.470)	(2.176)	(4.448)	(0.620)
Observations	16	17	17	15
R^2	0.185	0.902	0.670	0.885
Adjusted R ²	-0.019	0.869	0.559	0.840
Residual Std. Error	8.933 (df=12)	6.782 (df=12)	11.220 (df=12)	11.005 (df=10)
F Statistic	1.429 (df=3; 12)	2.586* (df=4; 12)	5.639*** (df=4; 12)	32.558*** (df=4; 10)
Note:			*p<0.1	; **p<0.05; ***p<0.01