Do Timeouts Matter? A Study of Euroleague Basketball*

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Abstract

This paper investigates the efficiency of time-outs in the EuroLeague, using Play-by-Play (PBP) and Box Score data from the 2021–22 to 2023–24 regular seasons. Our analysis of PBP data indicates that time-outs help mitigate losses during critical moments of a game but do not necessarily change its overall outcome. Additionally, evidence from Box Score data suggests that time-outs do not provide additional explanatory power beyond the standard four-factor model in determining team performance over the course of a season.

Keywords: Time-Out Efficiency, Euroleague Play-by-Play data, Euroleague Box-Score data.

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1 Introduction

Time-outs are a crucial aspect of in-game tactical management in basketball. Beyond organizing end-game plays in the final minutes, coaches often use time-outs to shift the game's momentum. In this paper, we analyze Play-by-Play data and overall season statistics, Box-Score data, from the EuroLeague to evaluate coaches' time-out strategies, their immediate effectiveness in altering game momentum, and their broader impact on team performance over a season.

The effectiveness of time-outs has been a subject of extensive debate among analysts, fans, and the media. Vergara (2025) and Eurohoops (2021), examined whether a time-out can halt a negative run, respectively using NBA data and 380000 game events from the 3stepsbasket basketball analytics platform [1], reaching different conclusions. The evidence in Vergara (2025), based on the definition of a run as an uncontested scoring stretch from one team, indicates that timeouts can be an effective tool for shifting momentum in a game with the timing and context of a time-out being critical factors of success. The evidence in Eurohoops (2021), based on the comparisons of runs identified as is a sequence of 6 possessions (3 offensive + 3 defensive) when one team outscores the other with 5 or more points[2], led to consistent results in favour of the strategy without time-out.

Coaches themselves have reflected on their time-out decisions. In an interview series by Eurohoops, CSKA Moscow's Dimitris Itoudis discussed how defeats offer opportunities to learn and adapt strategies, implicitly acknowledging the role of time-out decisions in game outcomes (Eurohoops, 2020).

Fan and media scrutiny of coaches' time-out practices is also prevalent. For example, ALBA Berlin's head coach, Israel Gonzalez, faced criticism during a challenging season where injuries and performance issues led to questions about his tactical decisions, including time-out usage. Gonzalez admitted thinking he might be fired after a particular game, reflecting the intense pressure coaches face regarding their strategic choices (Bild, 2023). As we will later demonstrate, Gonzalez's time-out efficiency was unmatched. It seems that tactical brilliance, when combined with the acute awareness of job security, can be a powerful motivator.

This study adopts a data-driven approach to investigate coaching practices related to time-outs, aiming to identify optimal moments for calling them to disrupt opponents' momentum and assess their overall significance in determining a team's success over a season.

[1] https://3stepsbasket.com/

[2] On top of that the 1st quarter was excluded and the game score difference was required to be 5 or less points at some point during the run

2 The Data and Their Analysis

To analyze the efficiency of timeouts and the empirical relationship between them and the wins of a team in a season we use two sets of data: i) play-by-play data to gauge the effectiveness of a timeout call, ii) game box-score data to extend the traditional four factors model of wins with a timeout efficiency factor. Our sample includes all regular season games from 2021-2022 to 2023-2024. Both sets of data are retrieved from the official Euroleague GameCenter API.[3]

2.1 Play-by-Play data

Play-by-Play data is a detailed log of all the events that occur during a basketball game. This data is recorded in real-time and includes information about every play, organized as follows:

- **Timestamp**: The exact time when each event occurs.
- **Play Type**: The type of action (e.g., shot attempt, foul, missed and successful shot, substitution, timeout).
- **Event Details**: Specifics of the event, such as the players involved, the outcome of a shot, the type of foul.
- **Score Updates**: Changes in the score as a result of the events.

2.1.1 Our Use of Play-by-Play data

In order to assess timeout efficiency, we use PbP data to compute functions of a team game score, both in general and around the timeout, that allows to gauge statistically the effectiveness of the coach call. We construct two new variables: i) *runs*, as in Vergara (2025), which are namely uncontested scoring stretches from one team. In this case, we label a timeout called by the coach of the team which is falling behind in the game as successful if it halts the ongoing run[4] in the first possession after the timeout. ii) *score differential impact*, which is the difference between points scored by a team and points conceded in the minute

[3] A full replication package in R is available upon request from the authors. Data have been retrieved using the R package **euroleaguer** and the unofficial API wrapper for 'Euroleague' and 'Eurocup' basketball API (*https://www.euroleaguebasketball.net/en/euroleague/*), which allows to retrieve real-time and historical standard and advanced statistics about competitions, teams, players and games.

[4] A run in basketball refers to a sequence of consecutive points scored by a team without interruption from the opponent. A team is said to be 'on-the-run' when it scores multiple points in succession, whereas it is 'off-the-run' when the opposing team goes on a scoring streak.

before and after a timeout. In this case, we label a timeout as successful if this difference is positive.

2.2 Game box-score data

We retrieve a rich set of game box-score variables through the API. This allows us to obtain a comprehensive list of elements, capturing the names of the teams and their respective coaches, individual player statistics (labeled `PlayerStats`) and aggregated team statistics (`TeamStats`) for all games.

2.2.1 Our Use of Box-Score data

Since play-by-play data only allow for a local measure of the impact of time-outs—by evaluating team performance before and after a time-out—we complement this with an analysis of their global effect on performance. To do so, we use box-score data to estimate the standard four-factor model of wins, introduced by Oliver (2004) and described in Winston (2009). We then assess whether adding a fifth factor, capturing time-out efficiency, provides additional predictive power for wins beyond the standard four factors.

3 Measuring time-out efficiency using Play-by-Play data

We use PbP data for descriptive statistics analyis first and then for inference. We first analyze the general features of time out calls. We analyze regular seasons data from three seasons excluding the last minute of the first three quarters and the last two minutes of the fourth quarter of each game. Figure 1 reports the share of total time-outs called in the three seasons (4300) when the team was home or away, or on the run or off the run.

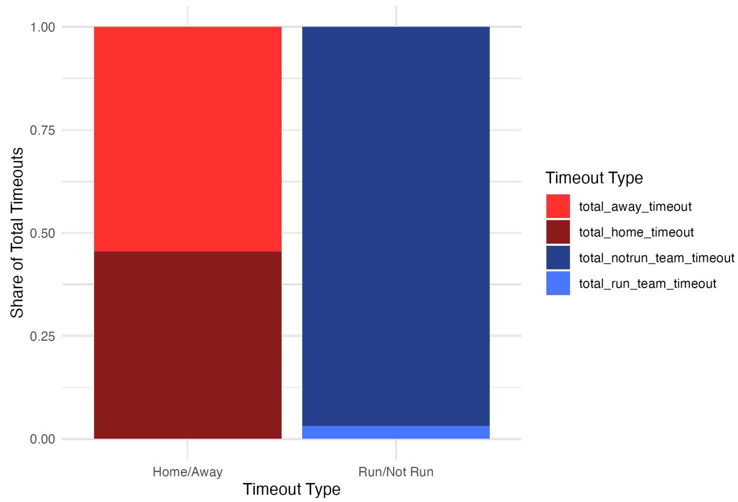

Figure 1: When Are Time-outs Called?

The evidence shows that being home or away makes very little difference in determining the coach's attitude toward time-outs, while being off the run is a crucial factor as over 95 per cent of time-outs are called when the team is off the run. Figure 2 allows to dig deeper into this evidence by looking at the frequency of time-outs called by the length of runs as measured in terms of consecutive points made by opponents.

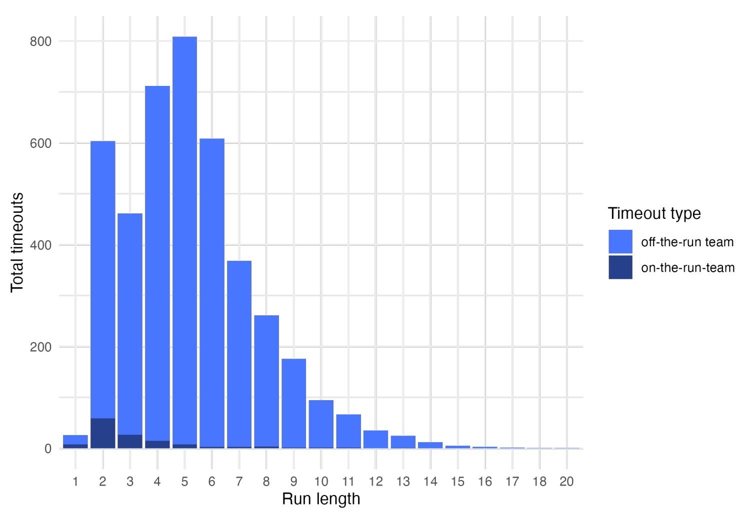

Figure 2: Timeout Types by Run

The distributions peaks at a mode at five points with most of the time-outs being called during runs from four to six points. Figure 3 confirms that this distribution is homogeneous for home and away games.

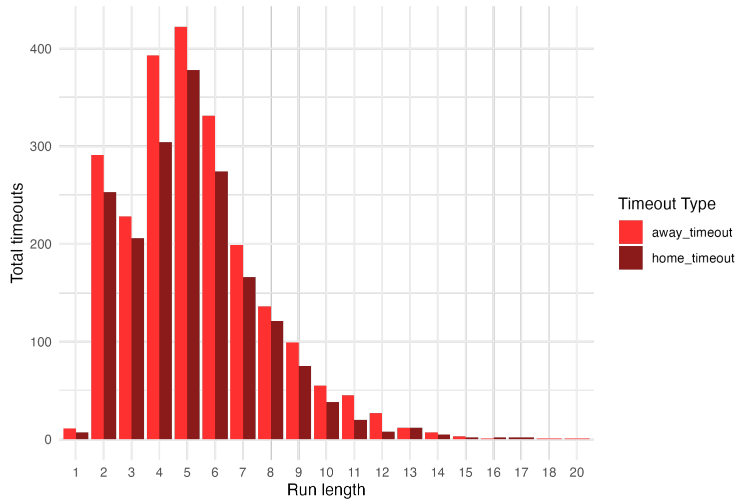

Figure 3: Home vs. Away Timeouts by run for team off-the-run

4 Is the Time-Out Cure Effective ?

Measuring the impact of time-outs using PBP data helps overcome one of the most fundamental challenges in econometrics: selection bias (Angrist and Pischke, 2009).

Consider the case where we aim to measure the impact of a treatment, represented by a binary variable that takes the value of one when the treatment is administered and zero otherwise, $D_i = [0, 1]$. The outcome of interest is the health status of an individual, Y_i. The treatment is administered in period 0, and its effect is measured in period 1.

Selection bias arises when we only observe the difference in average health between those who received the treatment and those who did not, while our real interest lies in estimating the average treatment effect on the treated:

$$\underbrace{E[Y_i|D_i = 1] - E[Y_i|D_i = 0]}_{\text{Observed difference in average health}} = \underbrace{E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 1]}_{\text{Average treatment effect on the treated}} + \underbrace{E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0]}_{\text{Selection bias}}.$$

The standard solution to this problem is to introduce randomization through experiments. Candidates for the treatment are randomly assigned to either a treatment group, which receives the intervention, or a control group, which does not. Due to this randomized assignment, selection bias is eliminated, and the observed difference in average health between the two groups accurately reflects the average treatment effect on the treated.

Now, consider a time-out as a treatment. The equivalent of an individual in our case is a team, and we consider teams in different years as different individuals.[5] By leveraging PBP

[5]For example, Real Madrid in season 2021-22, MAD^{2021}, is considered as a different team from Real

data, we can avoid selection bias because we observe team performance both in the presence and absence of time-outs. The equivalent of an individual in our case a The remaining challenge is defining an appropriate performance indicator.

We propose four indicators of performance:

- **Run Stoppage Efficiency ($\mathbf{RSE}_n$)**: Measures a team's ability to halt an opponent's scoring run of length n. Specifically, we examine the probability that an off-the-run streak of n points extends to $n+1$ points, comparing situations with and without a time-out.

- **Off-Run Adjustment (ORA)**: Captures how time-outs influence a team's ability to stop sustained scoring droughts. It is defined as the difference in the average (across all games played by each team in the regular season) length of off-the-run streaks in the minute before and after a time-out.

- **On-Run Adjustment ($\mathbf{ORA}^+$)**: Measures how time-outs affect a team's ability to sustain scoring momentum. It is the difference in the average (across all games played by each team in the regular season) length of on-the-run streaks in the minute before and after a time-out.

- **Score Differential Impact (SDI)**: Quantifies the overall impact of time-outs on game score. It is computed as the difference between points scored by a team and points conceded in the minute following a time-out, compared to the minute preceding the time-out.

4.1 The Graphical Evidence

We consider now the graphical evidence on the effect of time-outs on our four indicators of performance.

Figure 4 analyzes the Run Stoppage Efficiency, RSE_n, by reporting the probabilities with which runs of length n become runs of length $n+1$ in absence of a time-out call and in presence of a time-out call. These probabilities are computed on a team by team basis first and then they are averaged across teams.

Madrid in season 2022-2023, MAD^{2022}.

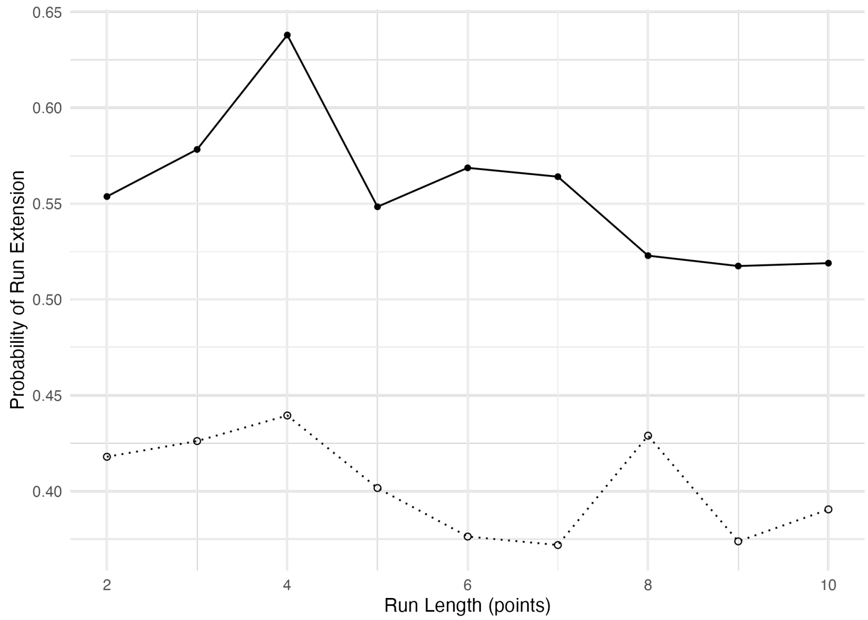

Figure 4: Run Stoppage Efficiency. The dashed line represents the probability that a run of length n extends when a time-out is taken, while the solid line represents the probability of extension in the absence of a time-out.

The evidence suggests that timeouts have a consistent impact on Run Stoppage Efficiency. In the absence of a timeout, the probability of extending a run increases from approximately 0.55 for runs of 2 points to a peak of 0.65 for runs of 4 points, before gradually declining to just above 0.50 for runs of 10 points. This pattern indicates a potential "hot-team" effect, where shorter runs (2–4 points) are more likely to extend, reinforcing momentum. However, when a timeout is taken, the probability of run extension decreases by at least 10 percentage points across all run lengths, with the largest impact—nearly 20 percentage points—observed for 4-point runs. The graphical evidence highlights that timeouts have a significant "cooling" effect, particularly in disrupting the natural increase in the probability of sustaining scoring streaks within the 2–4 point range.

The evidence from the Run Stoppage Efficiency is strong but breaking runs could not be decisive in terms of the impact on game outcomes. To gain some information in this direction we look at the impact of timeouts on Off-Run Adjustments and on On-Run Adjustments. Figures 5-6 show that time-outs have still some impact on the average length of off-the run and on-the run streaks, but the evidence is not as strong as that depicted in Figure 4 for the Run Stoppage Efficiency. When measured in terms of points scored around the coach calls, the impact of time-outs is not as strong as it is for the probabilities of breaking streaks.

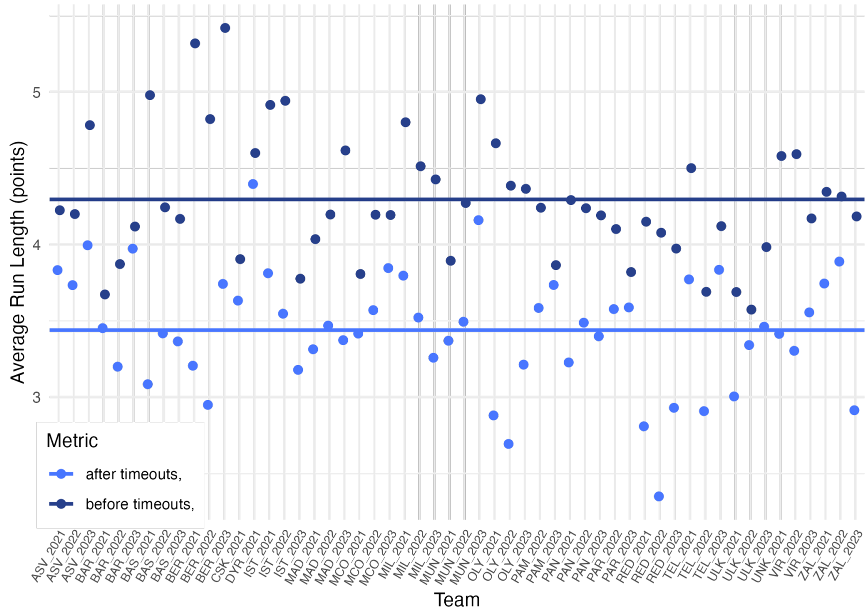

Figure 5: Average length of off-the-run streaks in the minute before and after a time-out

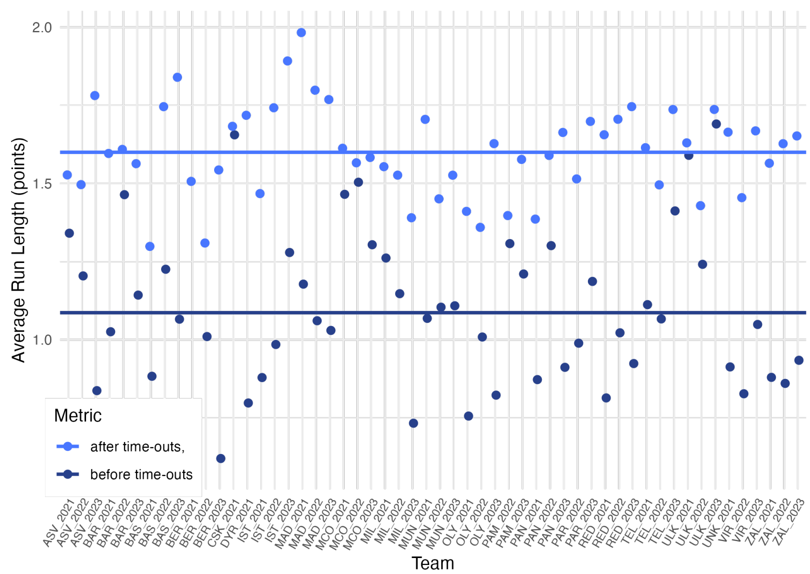

Figure 6: Average length of on-the-run streaks in the minute before and after a time-out

The most informative evidence on the impact of time-outs on the score is provided by the Score Differential impact reported in Figure 7. The Figure shows that the difference between points scored by a team and points conceded is narrower in the minute following a time-out compared to the minute preceding it. However, the score differential never turns positive on average for any team, indicating that time-outs help limit losses but do not turn games around.

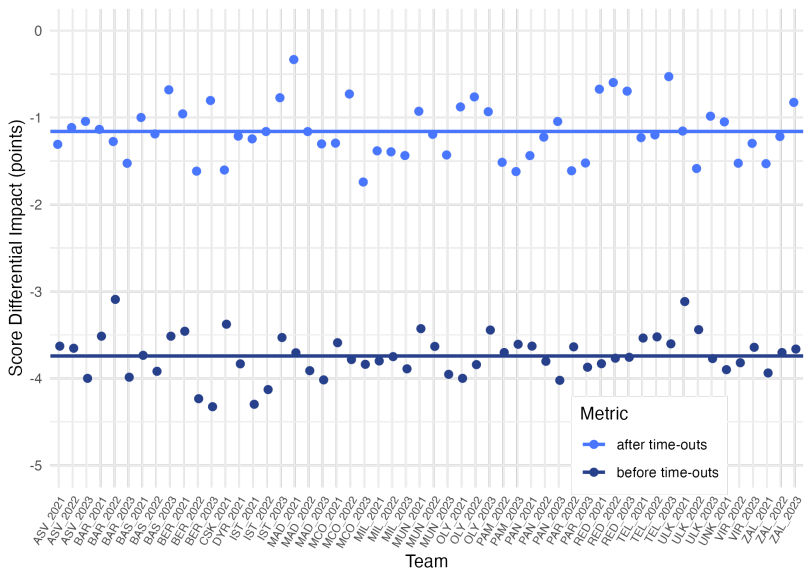

Figure 7: SDI: difference between points scored by a team and points conceded in the minute following a time-out, compared to the minute preceding the time-out

Table 1 complements the evidence by reporting the SDI for the top ten and the bottom ten teams in the league according to this criterion of time-out performance. Although SDI after time-outs are always smaller than SDI before time-outs, they never turn positive; not even for Israel Gonzalez, who we quoted in the Introduction, who is the most efficient coach in calling time-outs. It is also interest to note that there is no clear pattern of association between time-outs effectiveness and Standing of the team in the league at the end of the season. Again, Alba Berlin, the best performing team areound time-outs, came last in the regular season 2022-23.

Table 1: Score Differential Impact Before and After Timeouts (Top Ten and Bottom Ten Teams

Team	Year	Coach	SDI Before TO	SDI After TO	ΔSDI	Standing
BER	2023	GONZALEZ	-4.33	-0.804	3.52	18
MAD	2021	LASO	-3.71	-0.333	3.37	2
RED	2022	IVANOVIC, JOVANOVIC	-3.77	-0.598	3.17	11
RED	2021	RADONJIC	-3.83	-0.674	3.16	13
OLY	2021	BARTZOKAS	-4.00	-0.878	3.12	3
OLY	2022	BARTZOKAS	-3.84	-0.763	3.08	1
TEL	2023	KATTASH	-3.60	-0.529	3.07	6
RED	2023	SFAIROPOULOS, IVANOVIC	-3.76	-0.697	3.06	16
MCO	2022	S. OBRADOVIC	-3.78	-0.730	3.05	4
IST	2021	ATAMAN	-4.30	-1.25	3.05	9
VIR	2022	SCARIOLO	-3.82	-1.53	2.29	14
PAN	2021	PRIFTIS	-3.63	-1.44	2.19	17
PAM	2022	MUMBRU	-3.70	-1.52	2.19	13
MCO	2023	S. OBRADOVIC	-3.84	-1.74	2.10	4
PAR	2022	Z. OBRADOVIC	-3.64	-1.61	2.03	6
PAM	2023	MUMBRU	-3.61	-1.62	1.99	14
ULK	2021	DJORDJEVIC	-3.12	-1.16	1.96	14
ULK	2022	ITOUDIS	-3.44	-1.59	1.85	7
BAR	2022	JASIKEVICIUS	-3.09	-1.28	1.82	3
CSK	2021	ITOUDIS	-3.38	-1.60	1.77	6

4.2 The Statistical Evidence

In this section we support the graphical evidence of the previous section by applying to the analysis of team performance in presence or absence of timeouts the statistical evidence used to measure performance differences in the same subjects under different conditions in medical research (pre/post treatment effects), finance (comparing investment returns), and psychology (effect of interventions). In particular, we use two tests: the paired t-test, originally introduced by (Gosset, 1908),[6] and the Wilcoxon text (Wilcoxon, 1945).[7]

The **paired t-test** (also known as the **dependent t-test**) is a **parametric statistical test** used to compare the means of two related groups. It assesses whether there is a **significant difference** between the means of two dependent samples, typically taken from the same individuals before and after an intervention. The construction of the test is based on the assumptions of (i) paired observations, each data point in one sample corresponds to a data point in the other sample (e.g., value of an indicator in presence or in absence of

[6]See (Hogg et al., 2015) for a modern textbook treatment.
[7]See (Hollander et al., 1999) and (Gibbons and Chakraborti, 2010) for textbook treatment.

timeout), (ii) normality, the **differences** between paired observations should be **approximately normally distributed** and continuous data, and (iii) the measurement scale should be interval or ratio.

The paired t-test is based on the **difference** between paired observations:

$$d_i = X_{i,1} - X_{i,2}$$

where d_i is the difference between the paired values. The test statistic is calculated as:

$$t = \frac{\bar{d}}{s_d/\sqrt{n}}$$

where: $\bar{d}$ = mean of the differences, s_d = standard deviation of the differences, n = number of paired observations.

The test follows a ***t*-distribution** with $n - 1$ degrees of freedom.

The null hypothesis is that of no difference between means, our alternative hypothesis of interest is that the mean difference has a specific direction in the sense that time-outs have a positive impact on teams' performances and we therefore consider a one-tailed alternative.

The **Wilcoxon signed-rank test** is a **non-parametric** statistical test used to the same end with the paired t-tests, which is used as an alternative when the assumption of normality is violated. the key assumptions are still paired observations or continuos or at least ordinal data but the assumptions of normality is substituted with that of symmetry : the distribution of the differences between paired data should be approximately symmetric around the median. Given a set of paired observations $(X_{i,1}, X_{i,2})$, the test is constructed by computing the differences:

$$d_i = X_{i,1} - X_{i,2}$$

Ignoring zeros, the absolute differences $|d_i|$ are ranked from smallest to largest. The test statistic is given by:

$$W = \sum R_+$$

where R_+ is the sum of ranks corresponding to positive differences.

The distribution of W under the null hypothesis can be approximated using the normal distribution for large sample sizes. The null hypothesis is that the median difference between paired observations is zero, the alternative hypothesis is again one-tailed.

Table 2 reports the results of the implementation of the two tests to (i) the difference between paired Average length of off-the-run streaks in the minute before and after a time-out (**ORA**), (ii) the difference between paired Average length of on-the-run streaks in the minute before and after a time-out (**ORA**$^+$), and (iii) the difference between points scored and conceded in the minute before paired with the difference between points scored and conceded in the minute following a time-out (**SDI**).

Table 2: One-sided paired tests for (i) the difference between paired Average length of off-the-run streaks in the minute before and after a time-out (**ORA**), (ii) the difference between paired Average length of on-the-run streaks in the minute before and after a time-out (**ORA**$^+$), and (iii) the difference between points scored and conceded in the minute before paired with the difference between points scored and conceded in the minute following a time-out (**SDI**). The Table reports the paired t-tests (53 degrees of freedom) and Wilcoxon signed-rank tests,$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

	ORA	**ORA$^+$**	**SDI**
Paired t-test	$\frac{0.84}{0.06815}$ ***	$\frac{-0.51}{0.0356}$ ***	$\frac{-2.58}{0.05461}$ ***
Wilcoxon test	54^{***}	0^{***}	0^{***}

The statistical evidence confirms the graphical evidence as the null hypothesis is always rejected indicating that time-outs help limit losses with a statistically significant effect.

5 Is Time-Out Efficiency a Factor?

The evidence from Play-by-Play data on the effect of time-outs raises an intriguing question about their impact on team performance. While time-outs help to limit losses during critical moments of the game, they do not necessarily turn the game around. Can we provide evidence of their role as a factor in determining team performance throughout the regular season?

To address this question, we begin with a standard model that links basketball performance to a few key factors to then investigate whether a factor measuring time-out efficiency adds explanatory power.

Our benchmark model is a four-factor model of wins, which we specify by regressing teams' wins in the regular season on four indicators. These indicators are used to parsimoniously aggregate team statistics across different performance dimensions. The dimensions considered are Shooting, Turnovers, Rebounding, and Free Throws and Fouls.

The four factors are constructed for each team i entering the EuroLeague in season t as follows:

- $F1_{i,t} = EFG_{i,t} - OEFG_{i,t}$
  - EFG $= \frac{\text{Field Goals Made}+0.5\times\text{3-Point Field Goals Made}}{\text{Field Goal Attempts}}$
  - OEFG $= \frac{\text{Field Goals Made by Opponents}+0.5\times\text{3-Point Field Goals Made by Opponents}}{\text{Field Goal Attempts by Opponents}}$

- $F2_{i,t} = TPP_{i,t} - OTPP_{i,t}$
  - TPP $= \frac{\text{Turnovers}}{\text{Employed Possessions}}$
  - OTPP $= \frac{\text{Opponent Turnovers}}{\text{Acquired Possessions}}$
  - Employed Possession = Field Goal Attempts + 0.45 × Free Throws + Turnovers − Offensive Rebounds
  - Acquired Possession = Opponent Turnovers + Defensive Rebounds + Team Rebounds + Opponent Field Goal Attempts + 0.45 × Opponent Free Throws
- $F3_{i,t} = ORP_{i,t} + DRP_{i,t}$
  - ORP $= \frac{\text{Offensive Rebounds}}{\text{Total Missed Shots}}$
  - DRP $= 1 - \frac{\text{Opponent Offensive Rebounds}}{\text{Total Opponent Missed Shots}}$
- $F4_{i,t} = FTR_{i,t} - OFTR_{i,t}$
  - FTR $= \frac{\text{Foul Shots Made}}{\text{Field Goal Attempts}}$
  - OFTR $= \frac{\text{Opponent Foul Shots Made}}{\text{Opponent Field Goal Attempts}}$

The first factor captures the relative shooting efficiency, measured via the Effective Field Goal Percentage (EFG), compared to the Opponents' Field Goal Percentage (OEFG). EFG is calculated by appropriately weighting two-point and three-point shots made.

The second factor measures the relative efficiency of teams and their opponents in utilizing possessions, using Turnover Per Possession (TPP) as the efficiency indicator. Employed and Acquired Possessions are nearly equal by construction. A possession refers to the period during which one team controls the ball and attempts to score. It starts when a team gains the ball and ends when the team either scores or turns it over. A possession may also include multiple plays, and offensive rebounds can extend the same possession. Free throws are weighted at 0.45 in the definition of possession due to the occurrence of "and-one" situations.

The third factor accounts for the relative rebounding abilities by combining Offensive Rebound Percentage (ORP) and Defensive Rebound Percentage (DRP).

Finally, the fourth factor focuses on free throws and fouls, using the Free Throw Ratio (FTR), which is the ratio of Foul Shots Made to Field Goal Attempts. This factor captures both the effectiveness of drawing fouls on shooters and capitalizing on free throws.

To assess the explanatory power of the four factors in explaining team performance, we run the following regression on pooled cross-sectional data across all available seasons.[8]

[8] Pooling across different seasons increases the efficiency of the estimation without sacrificing consistency under the null hypothesis that the coefficients on factors are constant across seasons.

The following model, where the total number of wins for each team in each season W_{it} is linearly related to the four factors, is estimated:

$$\begin{aligned} W_{it} &= \beta_0 + \gamma_0 D_t^{2021-2022} + \gamma_1 D_t^{RUS} + \beta_1 F1_{it} + \beta_2 F2_{it} + \beta_3 (F3_{it} - 1) + \beta_4 F4_{it} + \epsilon_{it} \\ v_{it} &\sim N.I.D\left(0, \sigma^2\right) \end{aligned} \tag{1}$$

Note that in the 2021–2022 EuroLeague season, the expulsion of the Russian teams (CSKA Moscow, Zenit Saint Petersburg, and UNICS Kazan) resulted in a reduced number of regular-season games. The reduction in the number of games was different for the Russian teams and the other teams. Therefore, we introduce two dummies in our specification: $D_t^{2021-2022}$, which takes a value of 1 for all teams in the 2021-2022 season and 0 otherwise, and D_t^{RUS}, which takes a value of 1 for Russian teams in the 2021-2022 season and 0 otherwise.

The model has a very natural interpretation: all factors take the value of zero for the average team in the league, because the average team in the league performs exactly as the average opponent.[9] The constant in the regression captures the number of wins in the season of the average team, which is half of the game played, while the coefficients on each of the factors capture the contribution of each factor to explain for each team and each season higher number of wins with respect to the marginal team so the expected sign of the coefficients on the factors are positive for $F1_{it}, (F3_{it} - 1)$, and $F4_{it}$, in that Scoring Efficiency, Rebounding and Free-Throw efficiency contribute positively to performance, while it is negative for $F2_{it}$, in that turnovers contribute negatively to performance. Having established a baseline model of performance, we extend it to assess the potential impact of time-out efficiency by adding a fifth factor that captures how effectively a team uses its time-outs:

- $F5_{i,t} = SDIAT_{i,t} - SDIBT_{i,t}$
  - SDIAT = average point difference in the minute following a time-out, between the points scored by the team and the opponent
  - SDIBT = average point difference in the minute preceding a time-out, between the points scored by the team and the opponent

We then estimate the following augmented model:

$$\begin{aligned} W_{it} &= \beta_0 + \gamma_0 D_t^{2021-2022} + \gamma_1 D_t^{RUS} + \beta_1 F1_{it} + \beta_2 F2_{it} + \beta_3 (F3_{it} - 1) + \beta_4 F4_{it} + \beta_5 F5_{it} + \epsilon_{it} \\ v_{it} &\sim N.I.D\left(0, \sigma^2\right) \end{aligned} \tag{2}$$

[9] As a matter of fact $F3_{it}$ takes the value of 1 for the average team in the league and this is the reason why the variable included in the specification is $F3_{it} - 1$.

In this specification the significance of the coefficient on $F5_{it}$, which is included in the specification as de-meaned, captures the incremental contribution of time-outs efficiency as a factor for performance. The results from the estimation of the two models are reported in Table 3.

Table 3: The Four-Factor Model and the Five-Factor Model with a Time-out Efficiency Factor

	Dependent variable: W_{it}	
	Four-Factor Model	**Five-Factor Model**
Intercept	16.95***	16.97***
	(0.33)	(0.32)
$D_t^{2021-2022}$	-0.94	-0.96
	(0.60)	(0.60)
D_t^{RUS}	-2.83*	-2.98*
	(1.27)	(1.26)
$F1_{it}$	105.02***	103.50***
	(9.06)	(9.03)
$F2_{it}$	-101.49***	-100.51***
	(14.54)	(14.40)
$F3_{it-1}$	50.26***	52.28***
	(8.34)	(8.37)
$F4_{it}$	15.32*	17.07**
	(5.74)	(5.81)
$F5_{it}$		-0.99
		(0.69)
Observations	54	54
Residual Std. Error	1.94 (df = 47)	1.96 (df = 46)
Multiple R^2	0.86	0.86
Adjusted R^2	0.84	0.84
F Statistic	47.25 (6, 47)	41.68 (7, 46)

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

The estimation of the four-factor models reveals that all coefficients are statistically significant with positive values for the coefficients on $F1_{it}$, $(F3_{it}-1)$, and $F4_{it}$, and a negative value for the coefficient on $F2_{it}$. The factors explain .84 per cent of the variance of Wins. When the five-factor model is estimated, the null that the coefficient on the time-out factors is not statistically different from zero cannot be rejected, the estimates for all other coefficients are virtually unchanged, and the R^2 for the five-factor model is equal to that of the four-factor model. Therefore, the semi-partial R^2 associated with the time-out factor and capturing its marginal contribution to the overall explanatory power of the regression is zero. Figure 8 illustrates graphically the point showing the absence of a relationship between the residuals from the four-factor model regression and factor $F5_{it}$.

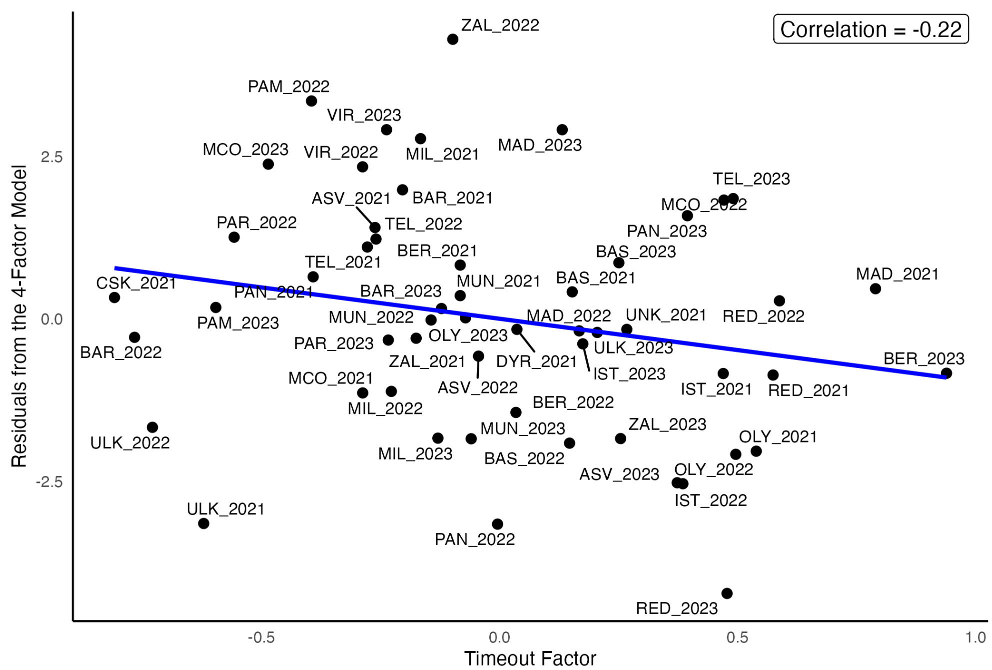

Figure 8: The 5-th factor (time-outs) and the residuals from the standard 4-factor model for Wins

Overall, we can conclude that time-out efficiency is not a factor to explain team performance in the regular season.

6 Conclusion

This paper evaluated Euroleague coaches' time-out strategies, focusing on their immediate impact on game momentum and their broader effect on team performance over a season.

Using Play-by-Play data, we find that time-outs are effective in disrupting opponents' momentum, particularly in stopping scoring runs of two to four points. However, when measured in terms of points scored around the coach calls, the impact of time-outs is not as strong as it is for the probabilities of breaking streaks. Moreover, an analysis of the *Score Differential Impact (SDI)*—the difference between points scored and conceded in the minute before and after a time-out—reveals a critical limitation. While time-outs help reduce scoring deficits, they do not, on average, reverse the score differential in favour of the calling team. In other words, time-outs mitigate losses but do not turn games around.

To assess whether time-outs contribute to long-term team success, we extend the standard *Four-Factor Model of Wins* by incorporating an SDI-based factor. The results show that the four standard factors already explain team performance well, and the time-out factor provides no additional predictive power.

So, do time-outs matter in the Euroleague? Yes, but only in a limited sense. Time-outs are useful for slowing opponents' momentum, but they do not significantly alter game outcomes or contribute to long-term team success.

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7 Appendix

Table 4: Team Names Mapping

Team Code	**Team Name**
ASV	LDLC ASVEL Villeurbanne
BAR	FC Barcelona
BAS	Baskonia Vitoria-Gasteiz
BER	ALBA Berlin
CSK	CSKA Moscow
DYR	Zenit St Petersburg
IST	Anadolu Efes Istanbul
MAD	Real Madrid
MCO	AS Monaco
MIL	AX Armani Exchange Milan
MUN	FC Bayern Munich
OLY	Olympiacos Piraeus
PAM	Valencia Basket
PAN	Panathinaikos OPAP Athens
PAR	Partizan Mozzart Bet Belgrade
RED	Crvena Zvezda Meridianbet Belgrade
TEL	Maccabi Playtika Tel Aviv
ULK	Fenerbahce Beko Istanbul
UNK	UNICS Kazan
VIR	Virtus Segafredo Bologna
ZAL	Zalgiris Kaunas