Momentum-stopping: Effects on Performance*

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Abstract

Does success breed success? Psychological momentum theory suggests that past achievements might influence future performance. However, distinguishing between psychological and strategic momentum — where a player's effort shifts based on relative position — is challenging. In this paper, using a novel dataset from professional *Counter-Strike: Global Offensive* matches, I focus on technical timeouts. These timeouts don't affect player position but may disrupt psychological momentum. I find that a winning [losing] team with significant momentum sees a 13 [11.7] percentage points increased chance of losing [winning] the following round after calling for such a timeout. This shows that psychological momentum significantly affects performance and that timeouts can reset the momentum.

JEL-Codes: D91, L83, Z20.

Keywords: Psychological momentum; Performance; Timeouts; Sports; Esports; Hot Hand.

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1 Introduction

Enhancing performance, whether in organizations or individual pursuits, is a universal objective. In this context, momentum—a phenomenon commonly discussed in sports and competitive settings—emerges as a critical factor. Momentum can be divided into two categories: strategic and psychological. Strategic momentum arises from changes in an individual's or team's relative position within a competition, influencing the equilibrium effort they provide. In contrast, psychological momentum, as defined by Cohen-Zada et al. (2017, p. 66), refers to "the tendency of an outcome to be followed by a similar outcome not caused by any strategic incentive of the players."

The definition of psychological momentum provided by Cohen-Zada et al. (2017) highlights the complexity of finding robust evidence of its existence —disentangling it from strategic momentum. Under these circumstances, laboratory experiments offer a suitable setting to study such phenomena. Descamps et al. (2022) conducted an experiment with a real effort task and found evidence that psychological momentum does affect performance.

Since external validity is often questioned in laboratory experiments, some studies have attempted to examine momentum in the field. As Palacios-Huerta (2023) discusses extensively, sports provide clean observability, high stakes, and expert players making decisions under a precisely defined rule set. These characteristics, among many others, make sports an ideal scenario for studying behavior. Consequently, many field studies on momentum use sports data. Several studies have explored these concepts in various contexts. For example, Cohen-Zada et al. (2017) look at bronze medal fights in Judo, a setting where one of the contestants reaches the fight coming from a win and the other coming from a loss. Conditional on the skill of the fighters, the contestant coming from a win is more likely to win the bronze medal fight. Other studies, like Gauriot & Page (2019) and Meier et al. (2020), deal with the endogeneity more directly by exploiting exogenous variation present in tennis matches.

Gauriot & Page (2019) utilize quasi-exogenous variation in winning probabilities based on whether a ball lands just inside or outside the court's line, as determined by Hawkeye technology. On the other hand, Meier et al. (2020) utilize exogenous variation in match interruptions stemming from the rules of tennis. Since interruptions do not affect the relative position of the player but might affect psychological momentum[1], this provides a way to separate between the two types of momentum —which Gauriot & Page (2019) are unable to do.

Both studies find that winning a point increases the probability of winning the next point. In Gauriot & Page's (2019) case, though they cannot definitively distinguish between strategic and psychological momentum, they find evidence suggesting psychological

[1] Since psychological momentum is likely related to a psycho-physiological response (Morgulev, 2023), it is possible that letting the individuals rest may "reset their mindset," lessening the impact of momentum on performance. Other studies have utilized timeouts to measure momentum, though Meier et al. (2020) are the first to address the endogeneity stemming from the timeout decision.

momentum is not the driver. Conversely, Meier et al. (2020) find an effect of psychological momentum on performance.

The present study makes a fourfold contribution. First, it leverages exogenous variations in match interruptions, like those used by Meier et al. (2020), to isolate psychological momentum and control for potential endogeneities present in other field studies. Second, unlike Meier et al. (2020), where interruptions were planned breaks at specific points in the match, the interruptions in this study can occur at any point in the game. This broader scope allows us to control for round-specific characteristics and measure momentum across different game stages, enhancing both the internal and external validity of the results. Third, the econometric approach employed enables the measurement of varying levels of momentum, facilitating estimation of the effects beyond single rounds or points. Finally, the present study looks at momentum in team tournaments, where the literature has struggled the most to find exogenous variation.[2]

While traditional sports have aided in the study of momentum, the rise of esports offers a novel opportunity. It introduced a competitive environment similar to traditional sports but with unique characteristics that can advance research on momentum's effect on performance. This present study separates psychological from strategic momentum while considering both the potential endogeneity of the timing of the timeout and the influence of the coaches. To do this, I constructed a dataset on professional Counter-Strike: Global Offensive (a popular video game) matches. Counter-Strike: Global Offensive has two types of timeouts: tactical and technical. Tactical timeouts are analogous to those in other sports. I will drop any cases of tactical timeouts and any rounds after since these timeouts are endogenous; the main focus will be on technical timeouts. Technical timeouts are called due to technical issues, like player latency. These technical issues are exogenous when controlling for round fixed effects.[3] Additionally, players and coaches are not allowed to speak during technical timeouts, unlike tactical timeouts. [4]

I find a large effect of timeouts on reversing the previous round's winner only when one of the teams has built enough momentum—won three or more rounds in a row—even when controlling for several characteristics. In this setting, a timeout called by the previous round's winner increases the probability of reversing the previous round's outcome by 13 percentage points (approximately 40% of the sample mean). Similarly, a timeout called by the previous round's loser increases the probability of reversing the previous round's winner by 11.7 percentage points. These results imply that when individuals build enough

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[2] The momentum in team sports literature mostly focuses on basketball and uses tactical timeouts to measure the effect of momentum (Permutt, 2011; Roane et al., 2004). However, tactical timeouts' timing is not exogenous —teams are more likely to call for a timeout when in a bad slump (Lloveras & Vollmer, 2021), and therefore, any change in performance may be attributed to a reversion to the mean. Additionally, some coaches may be better than others at inspiring the players and coordinating plays.

[3] The probability of having a technical issue in the second round is not independent of having had a technical issue in the first round. But if you compare within a round number, it is exogenous.

[4] All players have cameras on them, making monitoring easy. Also, the communications app players use records the voice communications of the players and coaches.

psychological momentum, their performance improves, and timeouts serve as a tool to reset the momentum.

The findings in this study show within-contest momentum for young adult men, wherein (Lloveras & Vollmer, 2021) past positive performance increases future positive performance within a match. Although I cannot test for the underlying mechanism, a review of other studies' results by Morgulev (2023) suggests psycho-physiological momentum to be the mediator in within-contest settings. The author indicates initial success [failure] has been shown to increase [decrease] testosterone levels (for men) and dopamine, which increases [decreases] confidence, risk-taking, and aggression, thereby enhancing [hindering] performance.

Then, to which other settings could this study's findings be extended? For example, the results found here could imply that the ordering of questions within a test can impact the final scores. Anaya et al. (2022) show evidence that ordering questions from easiest to hardest reduces the probability of abandoning the test and leads to the highest scores. Alternatively, imagine a trader who decides to invest in a particular share that promptly goes up. This could trigger a psycho-physiological response that increases their confidence, leading to increased risk-taking that day. Cueva et al. (2015) show that increased testosterone leads to further risk-taking, which they argue may destabilize markets.

2 Data

The data used in this study was extracted from HLTV and contains information on 170,812 rounds from 6,379 professional matches played between 2018 and 2023.[5] Of the 6,379 matches and 170,812 rounds, I used information from 5,431 matches and 35,974 rounds.[6] The data was gathered using the *awpy* library developed by Peter Xenopoulos.

2.1 Counter-Strike: Global Offensive overview

To understand the data, I will first lay out the basics of *Counter-Strike: Global Offensive*. It is a First-Person Shooter (FPS) multiplayer video game. In each match, two teams of five play against each other until either they win 16 rounds or, if there is a tie at 15-15, they win four out of the six rounds in overtime. There are two sides: Counter-Terrorist and Terrorist (Team A and Team B hereafter). Either side can win the round by eliminating every opposing team player. Team B can also win a round by planting and defending the bomb against Team A. If they manage to plant the bomb and it explodes, which happens 40 seconds after being planted, they win the round. On the other hand, Team A can win the round by defusing the bomb if Team B planted it. Rounds last one minute and fifty-five seconds by default. If Team B cannot plant the bomb and at least one player from each team is alive, then Team A wins the round. Teams switch sides after 15 rounds.

[5] A 2 to 5-star filter was used, which means all matches are from high-tier tournaments and teams.

[6] I explain the criteria for dropping the rounds and matches below.

Players can buy weapons, equipment, and grenades at the beginning of each round. Weapons vary from pistols, which are less expensive but also do less damage, to primary weapons, which are more costly but do more damage. Equipment refers to protective gear, which reduces damage taken, and defusers (only available to Team A), which diminish the time it takes to defuse a bomb. Each player can purchase different grenades, some of which deal damage while others can be useful to give themselves an advantage.

Players receive a certain amount of money each round to purchase weapons, equipment, and grenades; they can sometimes be given no money. The amount they receive depends on the number of rounds won or lost in a row, how many enemies they eliminated, and with what weapon they did so with. Players keep any money that they did not spend on previous rounds. They can also save some equipment from previous rounds if they are not eliminated. If the player survived the previous round, they would keep any weapons and protective gear in the condition they were in at the end of the round,[7] and any unused grenades they had. This will be important because I will control for the previous round, i.e., pre-treatment characteristics. If the player was eliminated in the previous round, they start the next with essential equipment: a default pistol and a knife.

2.2 Data gathering and management

Counter-Strike: Global Offensive has a practical data storage system. Every match produces a *demo file*, which contains the information needed to reproduce the game. Peter Xenopoulos has recently developed a library that can analyze *demo files* and turn them into readable components.[8] I have utilized his library to obtain most of the data I use in this study. In particular, I used the library to read the demos and obtain information on round characteristics, such as the round number and match score, and team characteristics, such as equipment value and money available. Most importantly, Xenopoulos's library allowed me to get information on when teams called technical or tactical timeouts. The library allows access to the in-game chat, which players need to use to call a technical timeout.

In the case of tactical timeouts, although it is possible to call one via the chat feature, it is not required. The command to call a technical timeout depends on the server's rules. For technical timeouts, most servers now require a command such as ".tech" or "!tech", but this was not always the case. The code and how I determined the type of timeout in these cases are available in Appendix A.

Timeouts can only happen between rounds, even if the technical issue occurred in the middle of the round. A round is only stopped and reset when a technical issue occurs before any player takes any damage. Technical timeouts last as long as the problem

[7] Protective equipment is deteriorated by taking damage. Both Kevlar and Helmet start at 100 when first bought. If the player survived the round with only 50 Kevlar left, he would begin the next round with 50 Kevlar. He may repurchase Kevlar to reach 100, although at full cost.

[8] A visual example of the data structure provided by the library is available in my GitHub repository. I reduced the example to the minimum information required to understand the structure. Every frame contains more information on every player on each team.

persists, whether 20 seconds or 30 minutes.[9] In some cases, the technical problems stop the recording of the game to the demo file, meaning that the recorded duration of the timeout does not necessarily represent the actual duration. Since I had to manually verify the types of timeouts, I also measured the duration and imputed incorrect values.

Since timeouts can only happen between rounds, all control variables must be from before the round starts. Otherwise, they could be affected by the timeout itself; that is, they would be bad controls. Therefore, I collected data on team characteristics from the last recorded second of each round. I will use the money available, equipment value, which sums up the value of weapons, protective gear, and utilities, and the number of defusers, armor, and helmets. Remember, players who avoid elimination keep all their equipment and money. Therefore, even though using the current round's characteristics would probably lead to a better prediction of the round winner, the previous round's features will still be helpful.

For the outcome variable, since I want to determine whether a timeout affects the game's momentum, I will define the dependent variable as a dummy variable, taking the value one if the team that lost the previous round wins the current one. The more rounds in a row that the previous round's winner has won, the more momentum they will have built. Therefore, one would expect the effect of a timeout to be stronger when, for example, the team accumulates three wins in a row than when they accumulate only one. I will run a specification interacting the technical timeout indicator with variables measuring the accumulated wins in a row.

Defining the outcome variable as taking the value one if the team that lost the previous round wins the current one comes with difficulty in creating the controls since they should depend on the previous round's winner and should not be affected by technical timeouts. For example, I want to control for the team's equipment value since having more weapons, defensive gear, defusers, and grenades can lead to a higher probability of winning the round. First, if I included the equipment value at the beginning of the current round, my estimates could be biased since these are outcomes. That is, having a timeout could affect the decision to buy equipment. Therefore, I need the equipment value to be measured before the timeout. Since timeouts can only happen between rounds, I measured the equipment value at the last recorded second of each round. I will call Team A's [Team B's] equipment value at the last recorded second of the *previous* round *Lag Equipment Value A [B]*. Since my interest variable is the probability of reversing the previous round's winner in the current round, I need the controls to depend on the previous round's winner. To do this, I define the control variable *Win Equipment Value* as follows:

$$\begin{aligned} Win\ Equipment\ Value = \quad & (Lag\ Equipment\ Value\ A * Lag\ A\ win) \\ & +(Lag\ Equipment\ Value\ B * Lag\ B\ win) \end{aligned}$$

Since *Lag A win* and *Lag B win* are mutually exclusive, *Win Equipment value* will measure the equipment value at the last recorded second of the previous round for the previous

[9] Therefore, teams are not forced to continue playing, and I will not be measuring the effect of, for example, continued connection issues. I also drop cases in which technical timeouts happen in contiguous rounds to avoid bias.

round's winner. I repeat this procedure with all other control variables when possible. A detailed description of all variables used in the analysis is available in Appendix B.

I define the variable *Technical Timeout* as taking the value one if there was a technical timeout called at the beginning of that round. I also created two additional variables called *Winner Technical Timeout* and *Loser Technical Timeout*. These are timeouts called by the previous round's winner and the previous round's loser. I make this distinction because it's possible having technical problems is frustrating for the player if they lost the previous round due to the issue. One might also suspect players are faking or "creating" technical issues to take a break if they are losing.[10] Separating the technical timeouts by the winner and loser of the previous round will address these potential problems. I used information on the players' names and their respective teams to define the team that called the technical timeout.[11] So, for example, the dataset indicates that player "A1", who belongs to "Team A," wrote "!tech" in the in-game chat after round 4 started, which they lost. Then, Loser Technical Timeout would take the value of 1 in round 5 of that game.[12]

Of the 170,812 rounds, I dropped some matches with data issues and matches where teams might not be providing their best effort. Some demo files are split into multiple parts. The parser might have trouble parsing one of the parts, so it won't end up in the final dataset. In 95 observations, the starting part of the match was missing. I dropped all observations from those matches because there was no information on the start of the match. I also dropped some matches in which any of the rounds showed a mismatch between the round number and the scores of each team. For example, if the round number is 10, but the teams have a combined score of 12, all rounds from that match are dropped. Finally, I dropped charity and show matches since players are likely applying a different effort than in other matches.

After cleaning the data from these observations, I begin to drop rounds for the sake of exogeneity. First, I drop any rounds after non-defined timeouts. These are longer-than-usual breaks in play that I didn't classify as tactical or technical timeouts based on the chat messages. These are likely tactical timeouts called via the in-game menu or usual breaks in play. I also dropped any rounds including and following consecutive technical issues. For example, if I classify rounds 3 and 4 in a match as having had a technical timeout, I drop them and any rounds following. This is to avoid measuring the effect of continued technical issues.

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[10] Nevertheless, faking technical issues is not an easy task. Additionally, since all of the technical timeouts used in the sample are before *any* tactical timeouts are used, there is no particular reason to fake technical issues because both teams have many tactical timeouts available.

[11] In some cases, I could directly match a message requesting a timeout to a team. This avoids any issues concerning the matching between players and teams. Additionally, cases in which I had both a team name and a player name showed that the matching led, in most cases, to the same results.

[12] Remember that rounds are not restarted unless no player has taken damage, so if the player calls a timeout in round 4, the timeout will take place before round 5.

I also drop any rounds including and following a tactical timeout, since these are endogenous interruptions.[13] Then, I drop any rounds right after a usual pause in play. For example, many tournaments allow teams some time after round 15. Finally, I only keep one round right after technical timeouts because all rounds after technical timeouts are outcome rounds.

Since manual verification is required to ensure that no tactical timeouts occurred during the round right after a technical timeout, I dropped rounds with technical timeouts where I could not find a video of the matches. Additionally, I dropped some rounds classified as technical timeouts where the pause duration was zero (via manual confirmation). In these cases, the technical issues occurred in the middle of the previous round, so the teams called for a pause before the start of the next one. However, the problem was solved quickly, so the technical timeout never started. Lastly, I drop all the first rounds of every match since there is no previous round's winner to reverse.

The working sample ends up containing information from 35,974 rounds from 5431 matches. In total, I use information from 562 technical timeouts. The summary statistics for the sample are available in Table 1. Note that, having dropped most of the rounds, technical timeouts are still unlikely to happen (only 1.6 percent of rounds). The first occurrence of a technical timeout in the sample used for regressions is right before round 3. On average, technical timeouts occur before the start of round 6. The last round in which a technical timeout occurs is round 25. Over 90% of technical timeouts occur before the start of the 10th round. In Tables B2, B3, and B4 of Appendix B, I provide detailed count of the number of technical timeouts used in the sample.

The only other fact worth commenting on is that the maximum timeout duration is 2511 seconds (over 41 minutes). This is an outlier, as shown in Figure 1. I will run robustness checks, dropping the 95th percentile, to verify that these observations do not drive my results.

[13] In Appendix C, I compare the effect of technical and tactical timeouts, so I keep one round right after tactical timeouts for those results only.

Table 1: Summary statistics

Variable name	Mean	SD	Minimum	Maximum
Technical timeout	0.016	0.124	0	1
Duration (s) of technical timeout (recorded in demo)	1.421	20.868	0	1,989.305
Duration (s) of technical timeout	2.097	32.691	0	2,511
Wins in a row	2.163	1.392	1	15
Score differential (winner - loser)	1.357	2.530	-14	15
Winner's equipment value	13,005.108	7,800.749	0	34,150
Loser's equipment value	1,609.275	3,784.770	0	28,000
Winner cash category	2.459	0.510	1	3
Loser cash category	2.344	0.516	0	3
Winner's defusers	0.670	1.081	0	5
Loser's defusers	0.086	0.364	0	4
Winner's armor	260.565	128.350	0	500
Loser's armor	30.987	72.376	0	500
Winner's helmet	2.239	1.680	0	5
Loser's helmet	0.214	0.595	0	5

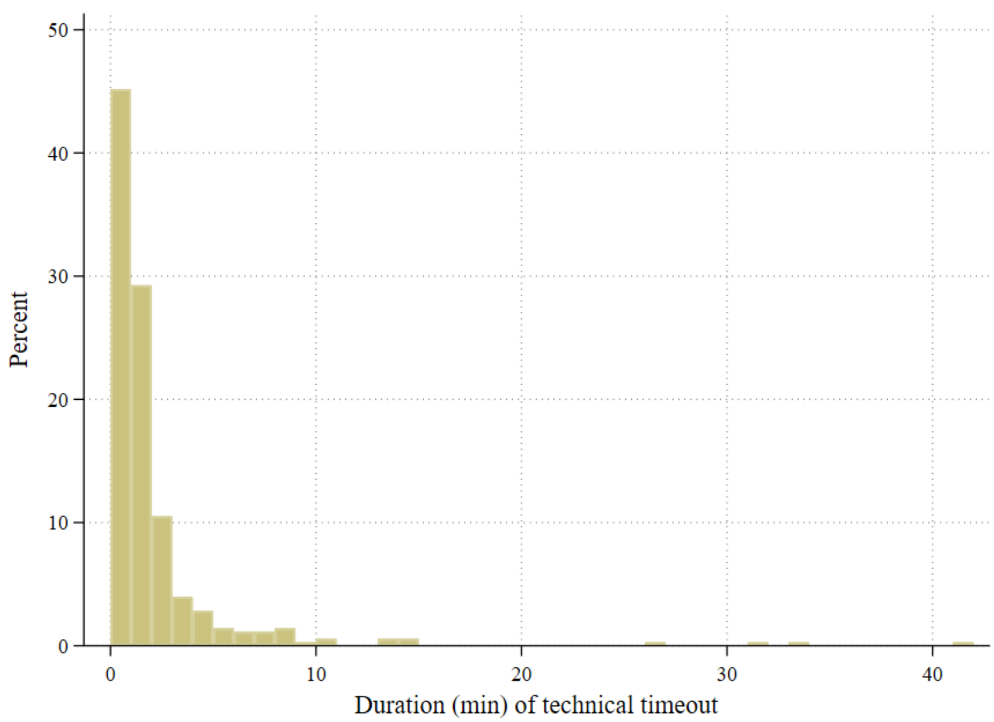

Figure 1: Distribution of technical timeout's duration

3 Estimation methodology and results

The econometric specification is as follows:

$$Y_{ir} = \alpha + \beta\ Technical\ Timeout_{ir} + \delta_i + \delta_r + \gamma X_{ir} + \epsilon_{ir} \tag{1}$$

where Y_{ir} takes the value one if the previous round's loser wins round r in match i; $Technical\ Timeout_{ir}$ takes the value one if there was a technical timeout before the start of round r of the match i; δ_i and δ_r are match and round fixed effects, respectively; and X_{ir} are a series of controls for round win probability. Since timeouts happen in between rounds, all controls are taken from the previous round, ensuring I don't include variables that might be outcomes themselves. I control for the equipment value, cash, defusers, armor, and helmets available, all measured in the previous round. I also include the accumulated round wins from the previous round's winner and the difference in score between the previous round's winner and loser.

Finally, X_{ir} also includes fixed effects for (i) the side that the previous round's winner is currently playing on interacted by the map being played, (ii) the team that won the previous round interacted with a year dummy, and (iii) the tournament the match was played on. The first set of fixed effects is meant to control for any biases towards one of the sides that may be present due to the layout and design of certain maps. For example, team A players may be favored to win rounds in certain maps, while team B players in others. The second set of fixed effects is meant to control for any team-related characteristics. For example, some teams may have more financial backing and can afford to provide their players with certain benefits that affect their performance. The last set is meant to control for anything that may have happened within a tournament. For example, it controls for the selection of teams that compete in the tournament.

The match and round fixed effects control for unobserved time-invariant match characteristics and round shocks common to all matches. Match fixed effects, for example, control for the players' individual factors, like experience and skill, which have been shown to affect psychological momentum (Cohen-Zada et al., 2017; Iso-Ahola & Mobily, 1980). Regarding round fixed effects, they control for any round-specific characteristics, helping avoid strategic momentum concerns by comparing equally numbered rounds with and without timeouts. To account for correlation between the outcomes of the rounds in one match, I cluster the standard errors in every regression at the match level. The results from estimating Equation 1 are shown in column 1 of Table 2. The coefficient for technical timeouts is close to zero and not statistically significant.

3.1 *Measuring momentum*

Determining whether momentum is present at a given moment is not clear-cut. Iso-Ahola & Dotson (2014) theorize that both the intensity and duration of the initial success are crucial factors. This would explain why Gauriot & Page (2019) find evidence against psychological momentum in tennis while Meier et al. (2020) find evidence in favor of it. The latter looks at the effect of winning an *unlikely* point—a precipitating event. Winning a point that is rarely won may trigger a confidence boost more easily than winning an average point. Multiple-point wins may be required before psychological momentum has an effect in tennis.

Without data measuring the intensity of each round win, I define momentum based on the number of consecutive round wins. The exact number needed to generate momentum is not determined. Iso-Ahola & Dotson (2014) argue that, when performing against opponents, psychological momentum will arise when the perception of oneself in relation to the opponent changes—when a player or team updates their belief on the probability that they will become victorious. Therefore, the crucial factor is how much of the positive signal is attributed to differences in skill as opposed to randomness or other factors such as a difference in equipment.

As in any real-life task, many factors affect whether a team wins a round in *Counter-Strike: Global Offensive* or not. A single win may easily be attributed to a fluke, either on your side or on the opponent's side. Additionally, given that there is momentum built-in to benefit the winning team after its first consecutive win, a second win may be attributed to the tactical advantage gained from the first win.[14] Though it is not clear when the "win" signal will start being attributed to the team's relative skill, it is reasonable to look for streaks of at least three wins.

Given the distribution of accumulated wins for technical timeouts (see Figure 2),[15] it would seem prudent to choose three accumulated wins instead of four or over, as using four would mean that the coefficient would be based on a low number of timeouts. Therefore, I define the dummy to take the value of one if the team gets three or more wins in a row. The results are available in column 2 of Table 2.

As momentum builds up before a timeout, its influence on reversing the outcome of the previous round becomes more pronounced. Timeouts after one or two round wins in a row have a negative (albeit not significant) effect, suggesting that if a team wins a round and then calls for a timeout, there's a higher chance that they will also win the next round. One team is known for this strategy, believing it makes their opponents dwell on their recent loss, thereby gaining an edge. On the other hand, timeouts after three or more consecutive wins have a positive coefficient. A technical timeout after three or more consecutive wins increases the probability of reversing the previous round's winner by approximately 12 percentage points.

[14] After a first consecutive win, the opponent team is given a small amount of cash at the start of the next round. This makes it harder for them to come back at first unless they have saved enough cash in previous rounds. As the number of consecutive wins grows, the losing team is benefited more. Note that this does not threaten exogeneity, as I am controlling for both the cash available to each team and the number of consecutive wins in a row.

[15] One might be tempted to think that if timeouts are exogenous, the distribution should be uniform. However, the probability of having technical issues in round n is not independent of having had problems in round $n-1$. Additionally, this distribution is plotted after dropping all rounds after tactical and non-defined timeouts and only keeping one round after technical timeouts. So, this is not the universe of technical timeouts.

In Table 3, I show the effect of timeouts by each level of accumulated wins in a row. The results are similar to the ones in column 2 of Table 2. Timeouts after just one win decrease the likelihood of reversing the previous round winner. When looking at two wins in a row, the effect turns positive, albeit small and insignificant. After that, it increases further and becomes significant at three accumulated wins. Timeouts after four or more wins in a row don't follow the same increasing pattern, likely due to the low number of observations used for each coefficient.

There are two other reasons that might explain the decreasing pattern after 3 wins in a row. First, since I am measuring momentum based on the effect the timeout has on the probability of reversing the previous round winner, the smaller effect size could be explained by a decrease in the effect of timeouts on momentum rather than on the effect of momentum on performance. That is, momentum may become harder to stop. Second, building too much momentum may lead to overconfidence, which then makes the players make mistakes, costing them their streak.

3.2 *Does the average effect found previously only tell part of the story?*

The team that requests the technical timeout may also play a significant role in influencing the outcomes. For instance, if Team A faces a technical issue mid-round that leads, in their view, to defeat, they might feel frustrated because rounds are only restarted if no player has taken any damage. Therefore, the effect could be biased downward when the previous round loser called the timeout. Column 3 of Table 2 shows evidence in favor of this.

Timeouts called by the previous round winner after three or more wins in a row increase the probability of reversing the previous round winner by approximately 13 percentage points (about 40% of the mean outcome). For timeouts called by the previous round's loser, the effect is slightly smaller: approximately 11.8 percentage points. Since timeouts do not affect strategic momentum, the results shown here imply that when teams build significant psychological momentum, they improve their performance, and timeouts can reset this momentum. In Appendix C, I compare the effect of technical timeouts and tactical ones and show how the endogeneity leads to biased results.

Table 2: Main results

Dependent variable	Reversing of the previous round's winner		
	(1)	(2)	(3)
Technical timeout	0.0206		
	(0.0253)		
Technical Timeout × 1-2 Wins in a row		-0.0467	
		(0.0329)	
Technical Timeout × 3+ Wins in a row		0.1244***	
		(0.0383)	
Winner Technical Timeout × 1-2 Wins in a row			-0.0487
			(0.0441)
Winner Technical Timeout × 3+ Wins in a row			0.1302**
			(0.0559)
Loser Technical Timeout × 1-2 Wins in a row			-0.0474
			(0.0481)
Loser Technical Timeout × 3+ Wins in a row			0.1176**
			(0.0508)
Observations	35974	35974	35974
Controls	Yes	Yes	Yes
Match fixed effects	Yes	Yes	Yes
Round fixed effects	Yes	Yes	Yes
Winner team-Year fixed effects	Yes	Yes	Yes
Side-Map fixed effects	Yes	Yes	Yes
Tournament fixed effects	Yes	Yes	Yes
Number of matches	5431	5431	5431
Mean outcome	0.32	0.32	0.32

Notes: Standard errors clustered at the match level are shown in parentheses. Controls include Wins in a row, Score differential, and the winner and loser's Equipment value, Cash, Defusers, Armor, and Helmet. *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

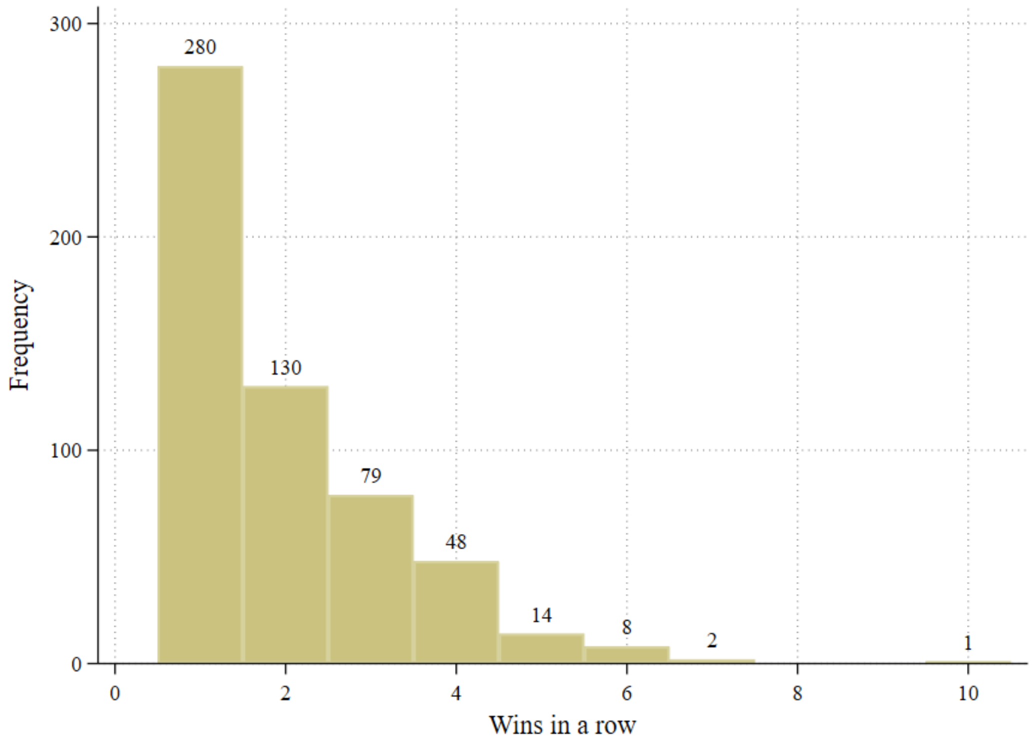

Figure 2: Distribution of accumulated wins for timeouts

Table 3: Further heterogeneity

Dependent variable	Reversing of the previous round's winner
	(1)
Technical Timeout * 1 Win in a row	-0.1093**
	(0.0472)
Technical Timeout * 2 Wins in a row	0.0330
	(0.0438)
Technical Timeout * 3 Wins in a row	0.1989***
	(0.0538)
Technical Timeout * 4 Wins in a row	0.0532
	(0.0667)
Technical Timeout * 5 Wins in a row	0.0804
	(0.1293)
Technical Timeout * 6 Wins in a row	0.0131
	(0.1545)
Technical Timeout * 7 Wins in a row	0.0962
	(0.1719)
Technical Timeout * 10 Wins in a row	-0.0775
	(0.0801)
Observations	35974
Controls	Yes
Match fixed effects	Yes
Round fixed effects	Yes
Winner team-Year fixed effects	Yes
Side-Map fixed effects	Yes
Tournament fixed effects	Yes
Number of matches	5431
Mean outcome	0.32

Notes: Standard errors clustered at the match level are shown in parentheses. Controls include Wins in a row, Score differential, and the winner and loser's Equipment value, Cash, Defusers, Armor, and Helmet.
*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

3.3 Robustness check

In this section, I test the robustness of the results found in column 3 of Table 2 and provide evidence in favor of the exogeneity of technical timeouts.

3.3.1 *Time placebos*

The estimates presented above could be capturing a trend in the data unrelated to technical timeouts and psychological momentum. For example, as Meier et al. (2020) suggest, teams could be adapting to the opponents' style of play after a few rounds. For

Table 4, I lead the technical timeout variable by one (column 1), two (column 2), and three rounds (column 3). That is, I replicate Table 2 having modified the treatment variable to be one to three rounds before its actual value. As I increase the lead, I drop the other observations. For example, if a timeout happened in the 4th round, the one-round lead technical timeout would take a value of one in the 3rd round. To estimate the effect of the leaded variable, I dropped the 4th round. This is because the 4th round would then be considered an outcome round.

Only one out of the six 3+ accumulated wins in a row interactions is statistically significant, and only two out of the remaining six coefficients are. This shows that, before the technical timeouts, there were no significant changes in the probability of reversing the previous round winner. Therefore, absent treatment, the treated matches behaved like controls.

Table 4: Results can't be replicated with time placebos

Dependent variable	Reversing of the previous round's winner		
	(1)	(2)	(3)
	One round lead	Two rounds lead	Three rounds lead
Winner Technical Timeout × 1-2 Wins in a row	-0.0240	-0.0541	-0.2073***
	(0.0555)	(0.0543)	(0.0640)
Winner Technical Timeout × 3+ Wins in a row	0.0891	0.0871	0.1338
	(0.0635)	(0.0833)	(0.0983)
Loser Technical Timeout × 1-2 Wins in a row	-0.0264	0.0065	-0.1942***
	(0.0581)	(0.0526)	(0.0714)
Loser Technical Timeout × 3+ Wins in a row	0.1554**	0.0584	0.0817
	(0.0641)	(0.0782)	(0.1024)
Observations	35463	35051	34733
Controls	Yes	Yes	Yes
Match fixed effects	Yes	Yes	Yes
Round fixed effects	Yes	Yes	Yes
Winner team-Year fixed effects	Yes	Yes	Yes
Side-Map fixed effects	Yes	Yes	Yes
Tournament fixed effects	Yes	Yes	Yes
Number of matches	5338	5251	5171

Notes: Standard errors clustered at the match level are shown in parentheses. Controls include Wins in a row, Score differential, and the winner and loser's Equipment value, Cash, Defusers, Armor, and Helmet. *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

3.3.2 *Could the results be due to outliers or data errors?*

As noted previously, there are a few outliers regarding the timeout's duration (see Figure 1). Additionally, some timeouts happened after round 15, when most tournaments let the teams have a break. Although I dealt with usual breaks by dropping any rounds after them, it could be that the break was not recorded. Both including these rounds or outliers could be driving the results. To check if this is the case, I reproduced the main specification using different samples to correct for these potential problems.

In column 1 of Table 5, I exclude timeouts above the 95th percentile to control for outliers. Since I also input some of the timeouts' duration, in column 2 I use the time recorded in the demo file. For column 3, I exclude all rounds after round 15. In all cases, the results for timeouts called by the previous round winner and loser after accumulating three or more wins remain large and significant.

3.3.3 *Is there evidence in favor of technical timeouts' exogeneity?*

Although technical issues would not be easy to fake and players have no reason to do so in the studied sample,[16] one might still wonder if they are actually exogenous. Regressing the technical issues on the controls shows that only five coefficients are significant, but both the statistical significance and the effect sizes are small (see Table 6).

Another check comes from looking at the correlation between the observed rounds and technical issues called by each team. If timeouts were exogenous, one would expect a team that won [lost] more rounds in the sample to have called more timeouts after winning [losing]. The correlation is approximately 0.87 and 0.82 for the previous round's winner and loser, respectively. Additionally, if players were faking the issues to stop the other team's momentum, one would expect the team that lost the previous round would disproportionately request more timeouts. This is not the case, as there are 310 timeouts called after winning a round and only 255 after losing.

[16] To see this, note that we dropped any rounds after tactical timeouts. Consequently, both teams have all their tactical timeouts available when the technical issues appear.

Table 5: Results are robust to multiple checks

Dependent variable	Reversing of the previous round's winner		
Sample	Excluding duration outliers (manual)	Excluding duration outliers (recorded time)	Excluding all rounds after round 15
Winner Technical Timeout × 1-2 Wins in a row	-0.0467	-0.0547	-0.0459
	(0.0450)	(0.0444)	(0.0449)
Winner Technical Timeout × 3+ Wins in a row	0.1138**	0.1257**	0.1240**
	(0.0566)	(0.0575)	(0.0577)
Loser Technical Timeout × 1-2 Wins in a row	-0.0362	-0.0462	-0.0517
	(0.0489)	(0.0498)	(0.0487)
Loser Technical Timeout × 3+ Wins in a row	0.1212**	0.1119**	0.1033*
	(0.0535)	(0.0530)	(0.0538)
Observations	35951	35949	34311
Controls	Yes	Yes	Yes
Match fixed effects	Yes	Yes	Yes
Round fixed effects	Yes	Yes	Yes
Winner team-Year fixed effects	Yes	Yes	Yes
Side-Map fixed effects	Yes	Yes	Yes
Tournament fixed effects	Yes	Yes	Yes
Number of matches	5427	5429	5431
Mean outcome	0.32	0.32	0.31

Notes: Standard errors clustered at the match level are shown in parentheses. Controls include Wins in a row, Score differential, and the winner and loser's Equipment value, Cash, Defusers, Armor, and Helmet. *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

Table 6: Controls can't predict technical timeouts

Dependent variable	Technical Timeout
Wins in a row=2	-0.0025
	(0.0018)
Wins in a row=3	-0.0024
	(0.0023)
Wins in a row=4	0.0022
	(0.0031)
Wins in a row=5	0.0002
	(0.0033)
Wins in a row=6	0.0058
	(0.0060)
Wins in a row=7	0.0047
	(0.0076)
Wins in a row=8	-0.0056*
	(0.0030)
Wins in a row=9	-0.0083**
	(0.0037)
Wins in a row=10	0.0284
	(0.0300)
Wins in a row=11	-0.0007
	(0.0045)
Wins in a row=12	0.0030
	(0.0045)
Wins in a row=13	-0.0044
	(0.0075)
Wins in a row=14	-0.0037
	(0.0070)
Wins in a row=15	-0.0211
	(0.0138)
Score differential (winner - loser)	-0.0004*
	(0.0003)
Winner’s equipment value	-0.0000
	(0.0000)
Loser’s equipment value	0.0000
	(0.0000)
Win team - Economy × Loss team - Economy	0.0039
	(0.0073)
Win team - Economy × Loss team - Half buy	0.0144
	(0.0227)

Dependent variable	Technical Timeout
Win team - Economy × Loss team - Full buy	-0.0058
	(0.0123)
Win team - Half buy × Loss team - Economy	0.0011
	(0.0057)
Win team - Half buy × Loss team - Half buy	0.0029
	(0.0022)
Win team - Half buy × Loss team - Full buy	0.0006
	(0.0024)
Win team - Full buy × Loss team - Full economy	-0.0097
	(0.0067)
Win team - Full buy × Loss team - Economy	0.0137
	(0.0213)
Win team - Full buy × Loss team - Half buy	0.0032*
	(0.0017)
Winner's defusers	-0.0006
	(0.0009)
Loser's defusers	0.0001
	(0.0024)
Winner's armor	0.0000*
	(0.0000)
Loser's armor	-0.0000
	(0.0000)
Winner's helmet	0.0006
	(0.0009)
Loser's helmet	-0.0009
	(0.0022)
Observations	35974
Match fixed effects	Yes
Round fixed effects	Yes
Tournament fixed effects	Yes
Winner team fixed effects	Yes
Number of matches	5431
Mean outcome	0.32

Notes: Standard errors clustered at the match level are shown in parentheses. *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

5 Conclusion

In this study, I exploit exogenous variation in match interruptions in professional *Counter-Strike: Global Offensive* matches to isolate the effect of psychological momentum and determine whether an interruption could reset it. I find that psychological momentum significantly drives performance. Controlling for many factors that could affect winning probabilities, teams that call for a timeout after accumulating three or more wins in a row have a decreased probability of winning the next round of 13 percentage points (almost 40% of the mean outcome). Similarly, teams that call for a timeout after accumulating three or more losses in a row have an increased probability of winning the next round of approximately 12 percentage points.[18] Furthermore, timeouts can reset the advantage gained from this momentum.

This study makes several contributions to the literature. Using technical timeouts provides exogenous variation in match interruptions that are not bound to a single point in time, like those found by Meier et al. (2020). This allows to control for round-specific characteristics and the measurement of momentum at different points in the match, increasing both internal and external validity. Additionally, it examines momentum in team settings, where the literature has struggled to find exogenous variation.

Unlike Meier et al. (2020), this study views psychological momentum as a sequence of positive outcomes rather than a precipitating event, showing robust field evidence that a string of successes leads to further success, validating Descamps et al. (2022). This study also replicates Meier et al. (2020)'s finding on the effect of timeouts on momentum. Both studies find that timeouts can halt momentum by using exogenous interruptions, and the results of this study present evidence consistent with two additional ideas—that momentum may become too strong to be affected by timeouts after many consecutive wins and that too much momentum may lead to overconfidence, which then leads to losing the streak. However, the evidence favoring these ideas is based on coefficients from a low number of observations, warranting further research to confirm its replicability. If confirmed, it would have significant implications for the momentum literature as it would suggest that (i) timeouts are only effective when momentum is not too prominent and/or (ii) that too much momentum may have a lower or negative effect.

Despite its contributions, this study has limitations. One limitation is that the effect found is an average across multiple individuals. Previous studies have shown that personal characteristics may influence the impact of psychological momentum (Cohen-Zada et al., 2017; Iso-Ahola & Mobily, 1980). I cannot provide any insights into the heterogeneity of the effect among the players, who are different in age, experience, and other characteristics. Another limitation is that the matches include only young adult males. Therefore, this study's findings only speak to the effect of momentum on the population that matches this description.

Considering the limitations, it is essential to reiterate the applicability of these findings to other settings. The matches used in this study are from professional esports teams. These teams earn their livelihood by competing in high-stakes tournaments. They experience pressures and dynamics similar to athletes in traditional sports. Hence, the findings

[18] Since technical timeouts only affect the psychological momentum component, the increased probability of reversing the previous round winner after a timeout comes from stopping psychological momentum's effect on winning the next round.

presented here pertain to esports and, more generally, to competitive settings where psychological momentum plays a significant role.

Beyond sports, psychological momentum could influence other fields, such as education and sales. For example, test scores might be affected by the order of questions, with students scoring the highest when the easiest questions are first (Anaya et al., 2022). Similarly, in sales, a string of successful sales could increase self-confidence and performance, as suggested by Bonney et al. (2020). However, their analysis also advocates too much success might lead to overconfidence and failure, implying firms should manage momentum to maximize productivity without leading to worse performance. This study suggests that timeouts could be a mechanism to halt momentum, with further research needed to determine whether and when momentum starts negatively affecting performance and the minimum timeout duration required to stop it.

Appendix A

This appendix provides a detailed procedure for constructing interest variables using a combination of Xenopoulos's library and external video sources. The replication files are available in my GitHub repository (Gómez Seeber, 2023).

Using Xenopoulos's library, I could determine if a timeout was called by looking at the in-game chat messages on each round and deviations in the time between rounds. To classify technical timeouts, I looked for any of the following commands on the in-game chat: ".tech", "!tech", "tec", ".tec", "tech", "!admin", or ".admin". If the command is found, the player that used it is saved, so we can later match the player to the team that called the timeout. In some cases, it was possible to find the team that called the timeout directly by looking for messages printed out by the console, such as: "Console: Team Astralis has called a technical pause".

One might worry that matching players to teams might lead to incorrect results if there are any issues with the data. Having cases where both a team and a player were found allows us to see how well the matching works. There were only a handful of instances where the team and the player led to different results. Manual verification showed that one of two things happened:

- i) Both teams had issues: one tried using an invalid command (in that tournament), and the other used the correct command afterward.
- ii) One team tried to call for a technical timeout with an invalid command, and the other team used the correct one so the match would be stopped.

For the second case, I manually imputed the teams that called the timeout as the one with the technical issues (which can be gathered from the other messages). In addition to searching for the commands mentioned above, I also search for two other types of messages: ones indicating that an issue occurred and ones indicating that a *tactical* timeout occurred. To search for rounds where a problem may have occurred, I look for words such as "crashed" and "work". Of course, this may lead to false positives, so I only define these rounds as technical timeouts as long as the messages indicate that there was an actual issue.

The reason I look for commands indicating a tactical timeout is to be able to identify rounds with tactical timeouts to (i) create the results in Appendix C, where I compare the coefficients of technical and tactical timeouts, and (ii) to drop all rounds after, and including tactical timeouts for the rest of the manuscript. Since tactical timeouts can also be called via the in-game menu, dropping rounds where I identified a tactical timeout to have taken place is not enough to ensure that the rounds in the sample don't include tactical timeouts. That is, tactical timeouts may have happened in the same round as technical timeouts.

I consulted YouTube videos or VODs (Video On Demand) of relevant rounds and matches to check whether this was the case. I used broadcasters' animations to determine if a tactical was called (see Figure A1 for an example). I excluded any observations where a tactical timeout followed or preceded a technical one.

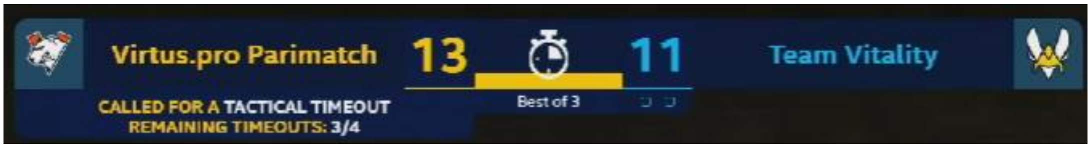

Figure A1: Typical broadcaster's animation on tactical timeouts

I created a "non-defined timeout" variable for instances with a longer-than-usual time gap between rounds, but neither a tactical nor technical timeout was explicitly identified. These are most likely tactical timeouts or usual breaks in play. I drop any instances of non-defined timeouts and any rounds afterward.

Appendix B

Table B1: Data description for selected variables

Variable	Description
Technical timeout	Dummy taking a value one if there was a technical timeout at the beginning of the round
Duration of technical timeout (seconds)	Duration of the technical timeout in seconds
Wins in a row	Amount of wins a row accumulated by the previous round's winner
Score differential (winner - loser)	Score differential between the previous round's winner and the previous round's loser
Winner's equipment value	Sum of weapons, grenades, defusers, kevlar and helmet value (in-game cost) for every player in the previous round's winner team
Loser's equipment value	Sum of weapons, grenades, defusers, kevlar and helmet value (in-game cost) for every player in the previous round's loser team
Winner's cash category	A categorical variable with 4 levels differentiating the previous round's winner team buying power based on the sum of cash for every player on the team. The levels are: less than 2000, between 2000 and 6000, between 6000 and 22000, and over 22000.
Loser's cash category	A categorical variable with 4 levels differentiating the previous round's loser team buying power based on the sum of cash for every player on the team. The levels are: less than 2000, between 2000 and 6000, between 6000 and 22000, and over 22000.
Winner's defusers	Sum of defusers for every player in the previous round's winner team
Loser's defusers	Sum of defusers for every player in the previous round's loser team
Winner's armor	Sum of armor (in-game cost) for every player in the previous round's winner team
Loser's armor	Sum of armor (in-game cost) for every player in the previous round's loser team
Winner's helmet	Sum of helmet (in-game cost) for every player in the previous round's winner team
Loser's Helmet	Sum of helmet (in-game cost) for every player in the previous round's loser team

Table B2: Technical timeouts count

Winner Technical Timeouts	Loser Technical Timeouts	Total Technical Timeouts
310	255	562

Note: There are three cases in which both teams requested a technical timeout. This is because both teams experienced technical issues.

Table B3: Technical timeouts count by accumulated wins in a row

Accumulated wins in a row	Winner Technical Timeouts	Loser Technical Timeouts
1	154	129
2	74	56
3	43	36
4	27	21
5	7	7
6	3	5
7	2	-
10	-	1

Table B4: Technical timeouts by momentum definition

Accumulated wins in a row	Winner Technical Timeouts	Loser Technical Timeouts
1-2	228	185
3+	82	70

Appendix C

This appendix compares the effects of technical timeouts with those of tactical ones. One detail worth noting before going into the results is that since teams can call tactical timeouts via the in-game menu, the timeouts I find are relatively few—only 364. This means that the coefficients calculated from these rounds, especially the ones in column 3, should be taken lightly.

Looking at the first column in Table C1, you can see tactical timeouts, like technical ones, seem to increase the likelihood of reversing the previous round's winner. The difference is that the effect is significant for tactical timeouts. We start seeing a divergence between technical and tactical timeouts when splitting the coefficient by whether the timeout happened after three or more consecutive wins. For technical ones, the coefficient is negative and insignificant for the 1-2 wins in a row interaction while positive and significant for the 3+ case. For tactical timeouts, the first one is positive and significant, while the 3+ interaction is positive - but smaller- and insignificant.

The two timeouts lead to different "optimal" strategies. If one were to look at tactical timeouts only, where endogeneity concerns are plentiful, the conclusion is that timeouts are best called after losing just a few rounds/points.[19] When measuring the effect using technical timeouts, the opposite is true.

Splitting the coefficients by the team that called the timeout, the winner coefficients have the same sign in both technical and tactical timeouts. The main differences are that the effect of the technical timeout for the 3+ wins interaction is significant and that the effect size for the tactical timeout is bigger in the 1-2 wins in a row interaction and smaller in the 3+ case. However, the differences are augmented when looking at timeouts called by the previous round's losing team. As in column 2, tactical timeouts show it's best to call a timeout after a few losses, while technical timeouts show it's the other way around.

These results underline the need for an exogenous interruption to measure the effect of timeouts on performance. The impact of coaches and the endogeneity of the timing provide biased estimates, and the conclusions drawn from looking at tactical timeouts differ from those obtained using an exogenous measure. Teams looking to maximize the effectiveness of their timeouts should only use them after multiple negative successive outcomes.

[19] This is from the point of view of the losing team. If the team that won the previous rounds were to be making the decision, the conclusions would be reversed.

Table C1: Technical and tactical timeouts

Dependent variable	Reversing of the previous round's winner		
	(1)	(2)	(3)
Technical timeout	0.0270		
	(0.0252)		
Tactical timeout	0.0558**		
	(0.0264)		
Technical Timeout × 1-2 Wins in a row		-0.0373	
		(0.0328)	
Technical Timeout × 3+ Wins in a row		0.1259***	
		(0.0380)	
Tactical Timeout × 1-2 Wins in a row		0.0900**	
		(0.0389)	
Tactical Timeout × 3+ Wins in a row		0.0248	
		(0.0359)	
Winner Technical Timeout × 1-2 Wins in a row			-0.0424
			(0.0448)
Winner Technical Timeout × 3+ Wins in a row			0.1455***
			(0.0555)
Loser Technical Timeout × 1-2 Wins in a row			-0.0353
			(0.0478)
Loser Technical Timeout × 3+ Wins in a row			0.1040**
			(0.0504)
Winner Tactical Timeout × 1-2 Wins in a row			-0.1135
			(0.0789)
Winner Tactical Timeout × 3+ Wins in a row			0.1048
			(0.1009)
Loser Tactical Timeout × 1-2 Wins in a row			0.1653***
			(0.0435)
Loser Tactical Timeout × 3+ Wins in a row			0.0133
			(0.0380)
Observations	36350	36350	36350
Controls	Yes	Yes	Yes
Match fixed effects	Yes	Yes	Yes
Round fixed effects	Yes	Yes	Yes
Winner team-Year fixed effects	Yes	Yes	Yes
Side-Map fixed effects	Yes	Yes	Yes
Tournament fixed effects	Yes	Yes	Yes
Number of matches	5437	5437	5437
Mean outcome	0.32	0.32	0.32

Notes: Standard errors clustered at the match level are shown in parentheses. Controls include Wins in a row, Score differential, and the winner and loser's Equipment value, Cash, Defusers, Armor, and Helmet. *Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

Statement

During the preparation of this work the author used GPT-4 in order to identify unclear sentences or ideas that required improved/ further explanation. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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