Do Incentives Shape Responses to Heat? Evidence from Track and Field

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Abstract

Extreme temperatures reduce human performance, but whether this reflects physiological limits or behavioral adjustment remains unclear. We test whether incentives shape responses to heat using collegiate distance running, where regular-season races reward qualifying times (absolute incentives) and championship races reward placement (relative incentives). Athletes run 0.2 standard deviations slower in championship races, consistent with strategic effort reduction under relative incentives, and also run slower on hot days. If responses to heat are partly behavioral, they should differ across incentive structures. Under absolute incentives, heat raises the cost of reaching a fixed threshold; under relative incentives, it is a common shock across competitors and should not affect effort. We find that the effect of heat is similar across race types and no statistically significant differences, indicating that temperature operates primarily through physiological channels. Two parallel shocks in 2020 that increased uncertainty around qualifying thresholds narrowed the performance gap across incentive schemes but left heat responses unchanged, reinforcing this conclusion.

JEL Codes: L83, M52, Q54, J24, D91
Keywords: relative and absolute incentives, heat stress, athletic performance, behavioral adaptation, technology shock

1 Introduction

Extreme temperatures reduce human performance. High temperatures slow manufacturing output (Somanathan et al., 2021), reduce the productivity of outdoor workers (LoPalo, 2023), and lower student achievement (Park et al., 2020). However, whether these effects reflect physiological limits or behavioral adjustment—individuals reducing effort when conditions become more costly—is unclear. This distinction has important implications for climate adaptation policy: if heat effects are physiological, incentive-based policies are unlikely to mitigate losses; if behavioral, productivity losses can be managed through incentive design.

If temperature responses are partly behavioral, the magnitude of the response should depend on how performance targets are set. When individuals are judged against a fixed standard—such as a qualifying time, production target, or test score—heat raises the cost of reaching that threshold and individuals may reduce their effort. However, when performance is evaluated relative to peers, temperature is a common shock affecting all similarly, which leaves relative incentives unchanged and should not induce changes in effort. These two incentive structures therefore generate distinct predictions for how performance responds to heat.

To distinguish physiological from behavioral channels, we use NCAA Division I collegiate distance running, which provides quasi-experimental variation in incentive structure across races. Regular-season races feature absolute incentives, where athletes aim to record one of the top qualifying times in their region. Championship races — regional preliminaries and the national championship — feature relative incentives, where athletes advance based on placement within their heat and aim to win the championship, making rank rather than time the primary objective. We use data on 41,678 performances across 15 national championships, 30 regional preliminaries, and 994 regular-season meets from 2010 to 2025.

Consistent with strategic effort reduction under relative incentives, athletes run approximately one-fifth of a standard deviation slower in championship races than in regular-season races—roughly nine seconds in the women's 5000 meters. Athletes also run slower on hot days. Because championship races occur later in the season, they are both slower and hotter, confounding the pooled relationship between temperature and performance. We therefore compare temperature effects within race type.

The effect of heat on performance is statistically indistinguishable across incentive structures. Athletes slow down on hot days by the same amount whether competing for qualifying times or for placement. This finding is inconsistent with behavioral adjustment: if responses to heat were driven by effort adjustment, we would expect a smaller temperature effect under relative incentives, where temperature is a common shock across competitors. Instead, the results indicate that heat operates primarily through physiological channels.

We further examine this conclusion using two coincident shocks in 2020—the cancellation of the outdoor season due to COVID-19 and rapid advances in carbon-fiber shoe technology—which increased uncertainty around qualifying thresholds. While this shock reduces the performance gap between regular-season and championship races, heat responses remain unchanged, reinforcing the physiological interpretation.

We contribute to a literature on the effects of temperature on human performance. Heat reduces output in manufacturing (Somanathan et al., 2021), interview settings (LoPalo, 2023), and learning (Park et al., 2020); raises the incidence of workplace accidents (Dillender, 2021; Ireland, Johnston and Knott, 2023); and reduces hours worked (Ireland, Johnston and Knott, 2024; Graff Zivin and Neidell, 2014), though gig workers paid by output may extend their labor supply (Papp, 2024). In athletic settings, heat slows track and field performance (Sexton, Wang and Mullins, 2022; Mullins, 2018) and worsens performance and injury risk in tennis (Burke et al., 2023; Picchio and Van Ours, 2025). Most of this work documents the existence of heat effects rather than identifying their channel. Our contribution is to test whether the response is behavioral or physiological by exploiting variation in incentive structure within the same set of athletes; the null we find under relative incentives points to physiological constraints as the dominant mechanism.

We also contribute to a long literature comparing absolute and relative incentive schemes (Lazear and Rosen, 1981; Holmstrom, 1982; Bandiera, Barankay and Rasul, 2005; Kerr, 1975; Ehrenberg and Bognanno, 1990), which has shown that the optimal structure depends on monitoring costs, risk preferences, and the scope for cooperation among peers. Our results add a new dimension to this comparison: we show that a salient shock to the cost of effort — extreme heat — does not interact with incentive structure. This suggests that the choice between absolute and relative schemes can be made on the trade-offs these papers identify, without further adjustment for the environmental conditions under which workers operate.

2 Incentive structure in collegiate athletics

Distance running provides a useful setting for studying incentives. Performance is precisely and objectively measured, athletes have information about competitors' times throughout the season, and incentive structures differ sharply and observably across race types. In addition, championship races introduce strategic considerations such as the cost of front-running, as leading requires breaking the wind for competitors and limits visibility of rivals. These features make the comparison across race types a clean test of incentive-driven behavior.

Track and field in the United States is a high-level competition in which student-athletes compete in a variety of events organized under the National Collegiate Athletic Association (NCAA). Our analysis focuses on men's and women's middle- and long-distance running events in NCAA Division I track and field. Specifically, we examine the 1500m, 3000m steeplechase, 5000m, and 10000m events, for a total of eight events when also separated by gender. These races provide a clear and quantifiable measure of performance and a well-defined progression of competition, making them ideal for studying incentives and effort responses. The outdoor collegiate track and field season runs from March to June, and consists of two main types of races: qualifying races and championship races. The incentives athletes face differ across these two race types.

Qualifying races are held at regular season meets from March to May.[1] The NCAA divides the country into two regions—East and West—roughly separated by the Mississippi River. In qualifying races, athletes aim to record one of the top 48 times in their respective region for a given event to qualify for the NCAA regional preliminary round. Because the qualifying threshold is determined only after all results are known, athletes aim to achieve their fastest possible time. We therefore classify regular season races as featuring an absolute

[1] There are also conference championships which are eligible for qualifying to the regional round. However, the incentive structure for conference championships is less clear. Most top athletes have already secured qualifying marks, so these meets emphasize team scoring and placement over time. Because the incentive structure is not clear, we exclude these races from our main analysis.

performance incentive.

Championship races include the regional (East and West) preliminary rounds and the national championship, held in May and June, respectively. In these races, athletes are primarily motivated by placement, rather than absolute time, and are therefore subject to relative performance incentives. The national championship is the final and most prestigious event, making it the clearest example of a race where athletes compete on position rather than to run the fastest possible time. Regional preliminaries are also prestigious and place-based. At each regional preliminary, 48 athletes per region (96 total per event) compete to advance to the national championship, which features final fields of either 12 or 24 athletes depending on the event.[2] In regional preliminaries, athletes compete in heats to qualify for the next round by finishing in the first "Q" places, or by being one of the fastest "q" athletes to have finished outside of the top Q in their heat. Athletes assigned to the final heat in each round therefore have the advantage of knowing the mark required to qualify on time and could collude to ensure the heat runs quickly enough to earn the "qs" (Hill, 2014). If athletes were primarily aiming for fast times, we would expect a disproportionate number of time-based qualifiers from the final heat. However, we see strong evidence that athletes focus on placement rather than time by examining qualifying behavior during heats. Figure A.2 shows that the proportion of automatic and time-based qualifiers does not differ by heat order, supporting the idea that regional preliminaries operate under relative performance incentives.

3 Data

Our athletics data cover middle and long distance races (1500m, 3000m steeplechase, 5000m, 10000m) in NCAA track and field from 2010-2025 sourced from TFRRS.org. We limit our sample to the national championship, the regional preliminaries, and any meet at which at least one athlete ran a time that was eligible for qualifying to a regional preliminary. We treat individuals as separate athletes for each event they compete in, and for most specifications, we further limit our sample to athletes who qualify for the regional preliminary at some

[2]The details of how qualifying differs by event are provided in Table A.1

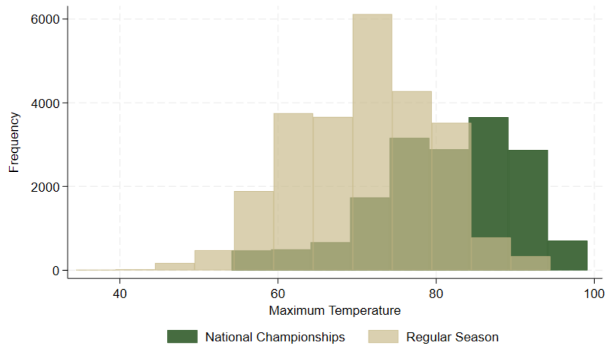

Figure 1: Temperature Distribution - Championship vs Regular Season

point in their career. We make this restriction for three reasons: first, we want to have a balanced sample to make comparisons between championship races and regular season races. Second, these are the athletes who are most motivated by the qualifying threshold. Third, we focus on races where athletes are attempting to run qualifying times, rather than small home meets where athletes might not be giving full effort.

Our final sample includes 39,615 athlete performances across 15 national championships, 30 regional preliminaries, and 988 regular season meets. Summary statistics for athlete characteristics and average times are given in Table 1. Championship races have a higher proportion of seniors (33.7%) than qualifying races (26.29%). As we also show in Figure 2, championship races tend to be slower than qualifying races for the flat events.

Climate data comes from NOAA weather stations, which are interpolated by inverse distance weighting to provide variables for temperature, precipitation, and wind speed at the site of each track. The distribution of temperatures is given in Table 1. Since championship races occur later in the year, they tend to have hotter temperatures. The temperature distributions are depicted in Figure 1. Races primarily occur in the evening, but we use the daily maximum due to not knowing the exact hour each race is held.

Table 1: Summary Statistics by Race Type

	Qualifying Races	Championship Races	All Races
Panel A: Race Characteristics			
Number of Meets	994	45	1039
Number of Individual Races	25014	16664	41678
Panel B: Temperature Distribution			
% <55	2.99	0.00	1.79
% 55 to 60	7.38	3.69	5.91
% 60 to 65	18.19	3.49	12.32
% 65 to 70	13.23	6.13	10.39
% 70 to 75	23.86	10.03	18.33
% 75 to 80	18.84	16.18	17.78
% 80 to 85	11.83	20.33	15.22
% 85 to 90	2.39	19.52	9.24
% >90	1.28	20.63	9.02

Notes: This table reports summary statistics for NCAA Division I distance races. Qualifying races include regular-season meets; championship races include regional and national championships. Average time Z-scores are standardized within event and gender.

4 Methodology

To investigate the role of absolute versus relative incentives, we test whether athletes perform differently in championship races. To do so, we estimate the following:

$$\begin{aligned} z_{ilt} = \beta_0 + \beta_1 Championship_{lt} + \phi_i + \tau_{year(t)} + \gamma Month_t \times \mathbf{1}(event_i \times gender_i) \\ + \delta_{region(l)} + \nu_{grade(ilt)} + \varepsilon_{ilt}. \end{aligned} \tag{1}$$

The dependent variable z_{ilt} is the standardized (z-score) race time for athlete-event i at meet m. Specifically, $z_{ielt} = (y_{ielt} - \mu_e)/\sigma_e$, where y_{ielt} is the raw race time and μ_e and σ_e are the event-gender-specific mean and standard deviation. This normalization makes performance comparable across events.

$Championship_{lt}$ is an indicator equal to one if race is at a championship meet. The specification includes athlete-by-event fixed effects ϕ_i, which absorb time-invariant ability within each event. To account for time-invariant differences across location, we include region fixed-effects, $\delta_{region(l)}$, for the four census regions (West, Midwest, North East and

South). Year fixed effects $\tau_{year(t)}$, academic grade fixed effects, $\nu_{grade(it)}$ and an event specific month trend $\gamma Month_t \times \mathbf{1}(event_i \times gender_i)$ are also included.

Next, we estimate the effect of temperature on performance. In order to accommodate a non-linear effect of temperature, we use a binned approach.

$$
\begin{aligned}
z_{ilt} = \beta_0 + \sum_{j=1}^{J} \beta_j temp_{j,cd} + \phi_i + \tau_{year(t)} + \gamma Month_t \times \mathbf{1}(event_i \times gender_i) \\
+ \delta_{region(l)} + \nu_{grade(ilt)} + \beta X_{lt} + \varepsilon_{ilt}.
\end{aligned}
\tag{2}
$$

Daily maximum temperature is divided into 5°F bins to allow for flexible nonlinear effects ($<$ 55°F, 55–60°F, 60–65°F, 65–70°F, 70–75°F, 75–80°F, 80–85°F, 85–90°F, $\geq$ 90°F). The 70–75°F bin is omitted as the reference category, leaving eight bins. X_m contains weather controls (precipitation and wind) at the location on the day of the meet.

To test whether incentive structure matters, we interact temperature with an indicator for being in a championship race. In order to preserve power in this subgroup analysis, we utilize a quadratic polynomial for temperature (see Equation 3). For each type of race, the incentives differ. In the regular season, athletes are running to set personal bests or to qualify for the regional round of championships. At regional preliminaries, athletes advance primarily by placing well in their heat, although they have some incentive to frontrun so that their heat is the fastest. A similar feature occurs at nationals in the semifinal round of the 1500 and steeplechase, but in the final, the only meaningful statistic is place, not time.

$$
\begin{aligned}
z_{ilt} = \beta_0 + f(temp_{ilt}) \times championship_{lt} + \phi_i + \tau_{year(t)} \\
+ \gamma Month_t \times \mathbf{1}(event_i \times gender_i) + \delta_{region(l)} \\
+ \nu_{grade(it)} + \beta X_{lt} + \varepsilon_{ilt}.
\end{aligned}
\tag{3}
$$

5 Results

5.1 Incentive structure and performance

Figure 2 shows the time difference in athlete performances during championship races, after controlling for year and athlete-event fixed effects. The outcome variable is a Z-score of race time, so a positive coefficient represents a slower time. For all flat distance events, athletes run more slowly in the championship races than they do in early season qualifying races. The magnitude of the change is similar between regional and national races, causing us to believe we can group them together for analysis. This effect is largest for the 5000 and 10000, with athletes running about 20% of a standard deviation slower. In the 1500, athletes slow down in championship races, but to a lesser extent.

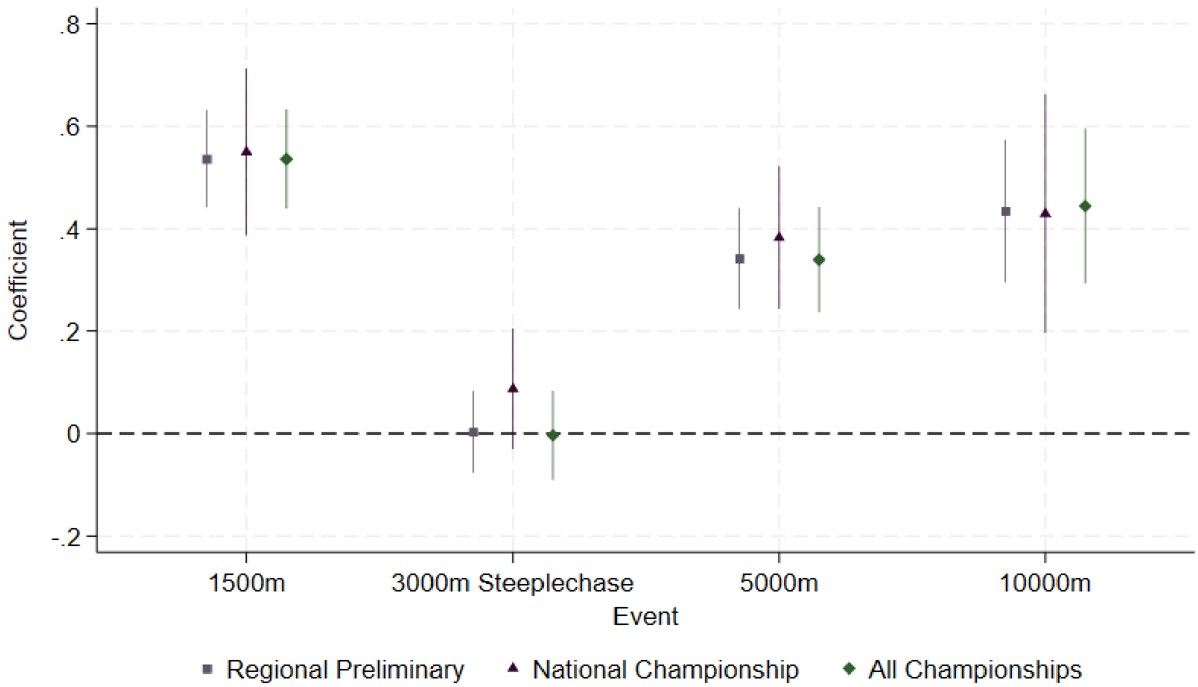

Figure 2: Championship vs Qualifying Races

Notes: Estimated coefficients for an indicator for each type of race. Each regression includes individual athlete fixed effects. Error bars depict a 95% confidence interval.

A number of factors can contribute to this phenomenon. "Frontrunning" is costly. As such, athletes try to avoid being the first in a pack. Not only does the athlete in first break the wind for the following competitors, the mental cost of not seeing your competition can wear down the race leader. In order to overcome this aversion, most regular season races will employ a pacer with the objective of leading the race for a prespecified distance in order to ensure all competitors start quickly. Anecdotally, athletes in a qualifying race are more likely to collaborate to maximize their time even after the pacer steps off. In a championships races, pacers are not utilized.

The steeplechase behaves differently from the other events. While the negative costs associated with frontrunning still apply, they are offset by the benefit of having a clear line of sight to the barriers. As such, athletes are more likely to consider it a good strategy to lead a championship steeplechase race. Furthermore, in qualifying races, steeplechasers have higher risks with attempting to run their fastest. In a flat event, becoming too tired results, at worst, in a few uncomfortable laps or the shame of dropping out of the race. In the steeplechase, becoming too tired could result in clipping a barrier and potentially derailing the season with an acute injury.

Figure 3 depicts the coefficients on the temperature bins for all performances. We find that extreme temperatures, both hot and cold, serve to slow down finishing times of athletes. This most concise specification serves as a bellwether of our results to previous studies, and reaffirm that high temperatures result is slower race performances.

In Figure 4, we present the average and marginal effects of temperature separately for qualifying and championship races. While championships races are clearly slower than qualifying races, the marginal effect of extreme high temperature is the same across incentive structures.

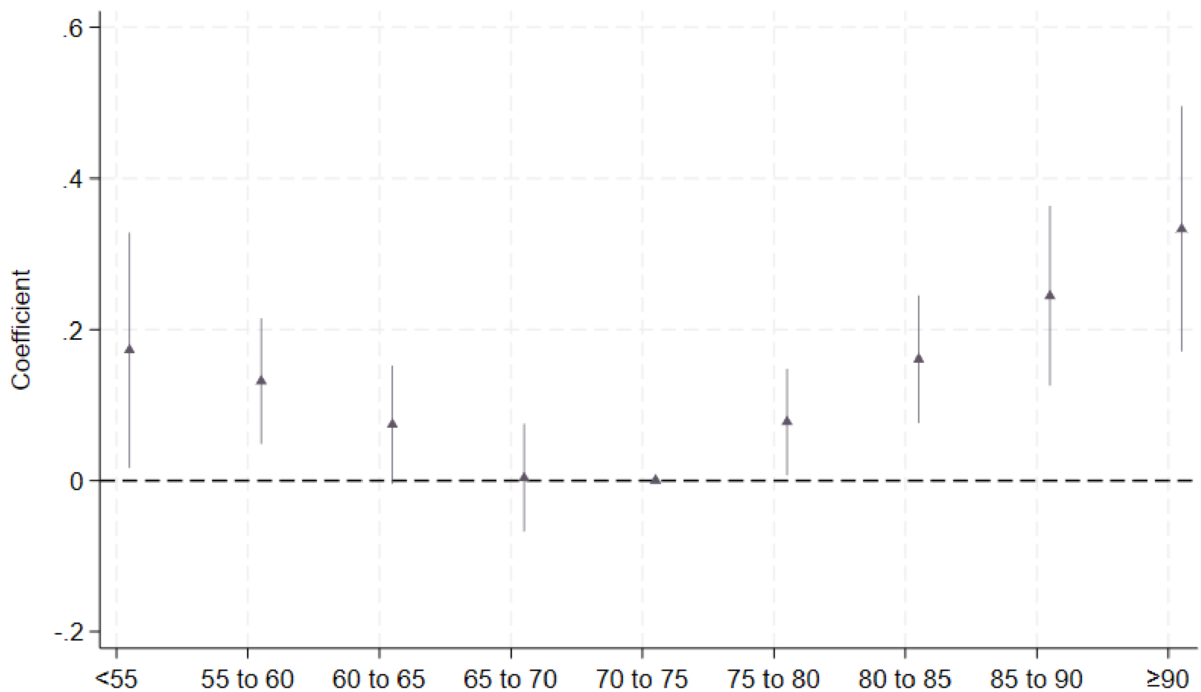

Figure 3: Effect of Temperature

Notes: Estimated coefficients for the effect of temperature on athlete performance. Error bars denote the 95% confidence interval.

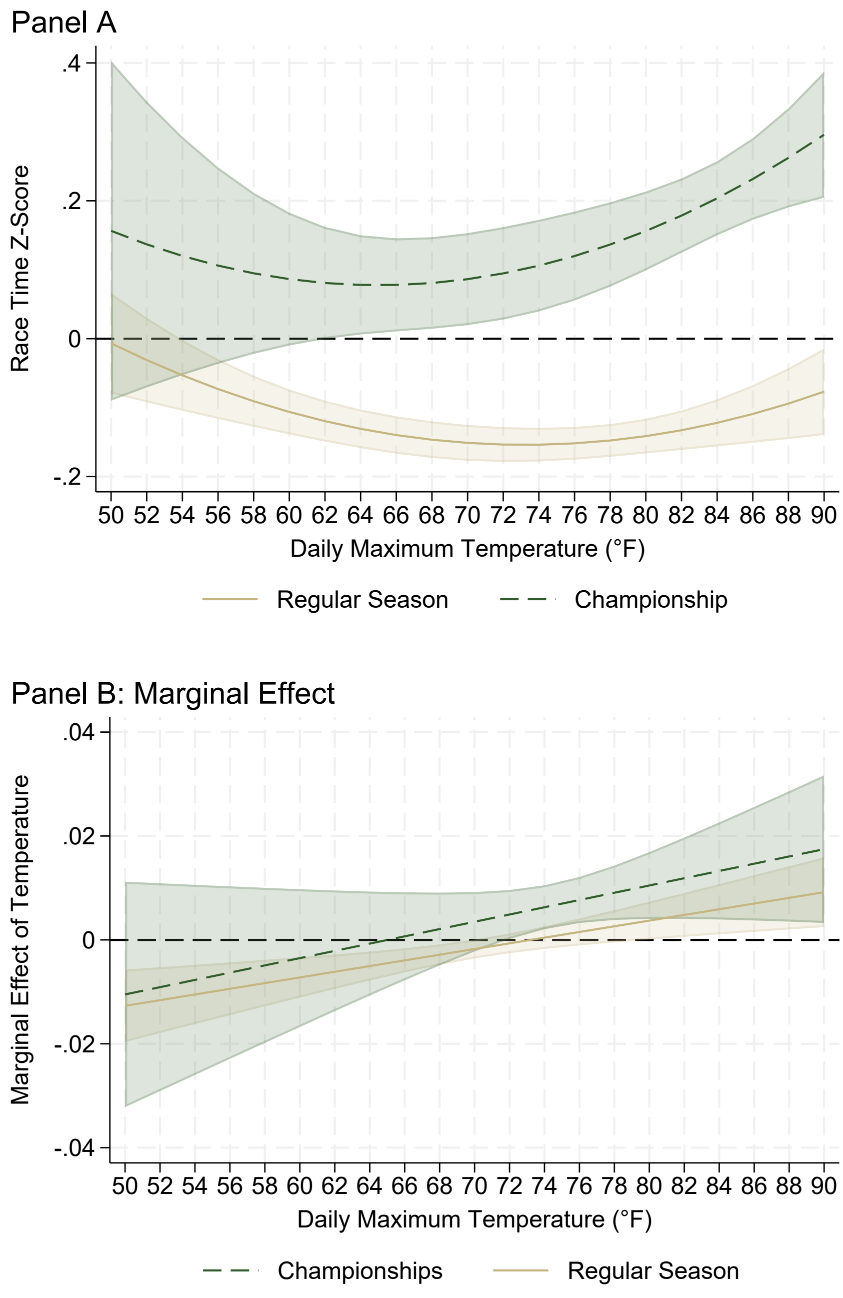

Figure 4: Effect of Temperature - Continuous

Notes: Estimated coefficients for the effect of temperature on athlete performance. In Panel A, error bars denote the 95% confidence interval. The outcome mean is -0.002.

6 The role of uncertainty in performance targets

One concern with absolute performance targets is when they create no marginal incentive beyond a threshold. For example, top performing sales workers may have no incentive to achieve beyond their monthly sales target if the activity is not rewarded (Kerr, 1975). An issue can arise if the incentive discourages maximal effort among high performers who have already achieved the standard.

In earlier sections, we showed that athletes run faster under absolute incentives during regular season races than under relative incentives in championship competition. A concern, however, is whether absolute thresholds induce strategic effort reduction among high-performing athletes—especially on hot days.

This section examines whether uncertainty about the qualifying threshold mitigates this concern. In NCAA track, athletes do not observe the qualifying cutoff in advance and must infer it from historical benchmarks and the times run so far in the season. The regular season is long enough that most athletes will have at least two attempts to run a qualifying time. While qualifying standards were relatively stable prior to 2020, two coincident shocks in 2020—the cancellation of the outdoor season and major advances in shoe technology—substantially increased uncertainty about the final qualifying times in 2021-2025.

In 2020, the NCAA outdoor season was canceled due to the COVID-19 pandemic, disrupting normal training and competition schedules and eliminating an entire season of performance information. In addition, significant advances in racing shoe technology—most notably the introduction of carbon-fiber plates and new mid-sole foams—substantially reduced the energetic cost of running and led to faster race times across events. Together, these shocks contributed to both a discrete shift and increased year-to-year volatility in the qualifying times required to advance to regional preliminaries. Importantly, these shocks did not alter the structure of qualification itself, which continued to depend on achieving an event-specific time threshold, but rather affected athletes' ability to predict the final cutoff ex ante.

Figure 5 demonstrates how the break from competition and improvements in shoe technology resulted in an increase in uncertainty around the threshold to qualify for the regional preliminary. As a result of this uncertainty, we observe a level shift and trend break in the qualifying time. After 2020, the final qualifying time is less predictable, so fewer athletes have the luxury of "easing into" the regional meet. As such, the incentive of a regular season race becomes even more of an absolute bar, as athletes must run as fast as they can to improve their chances of qualifying.

We test for a behavioral response to this shift in two ways. In Figure 6, we recreate Figure 2 splitting the sample around 2020. How the championship gap changes is not clear beforehand. If both regular season and championship races improve in percent terms, the gap will remain the same. If both experience a level shift (i.e. a 10 second improvement) the gap will appear smaller. If regular season races become faster relative to championship races, the gap could increase. We find that championship races after 2020 are less slow compared to the preceding years. This result suggests that being shocked out of the equilibrium for qualifying times also resulted in a shock to the strategies employed by championship athletes.

We also test whether athletes are more immune to temperature shocks when the qualifying threshold is more uncertain. In Figure 7 we recreate Figure 4 splitting the sample around 2020. The sample is expanded to include athletes who were close to the qualifying threshold, in order to not select our sample for having performed successfully in the heat. We find that while athletes run faster after 2020, the marginal effect of temperature remains the same, consistent with our previous results that incentive structure does not alter the effect of temperature.

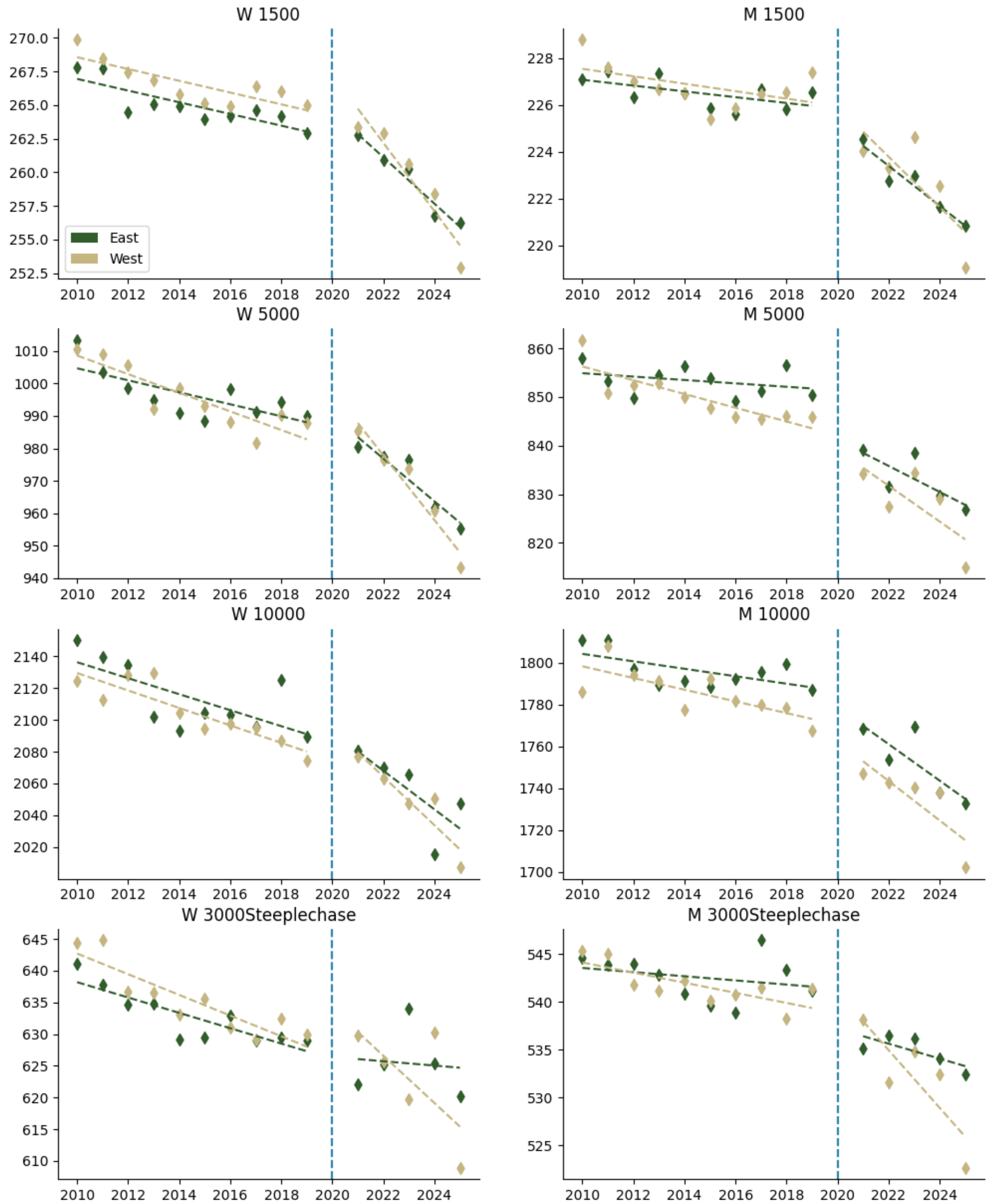

Figure 5: Qualifying Time Trends

Notes: Plot of qualifying times by region in each event. Trend lines are estimated separately before and after 2020.

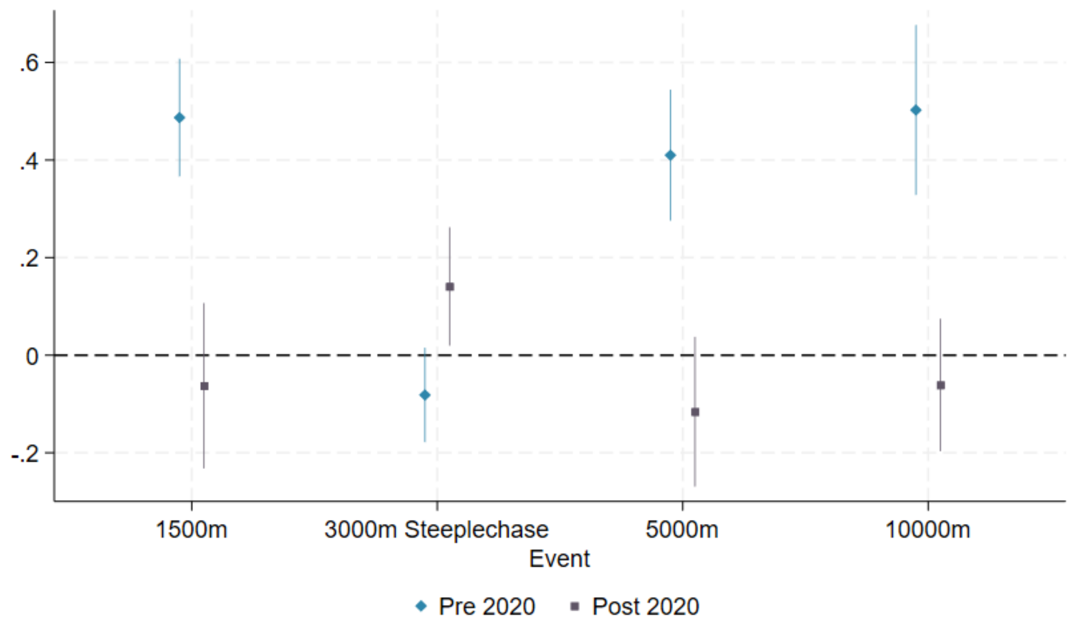

Figure 6: Effect of Championship Races Before and After 2020

Notes: Estimated coefficients for the mean difference in performances in championship races by time period. Error bars are 95% confidence intervals.

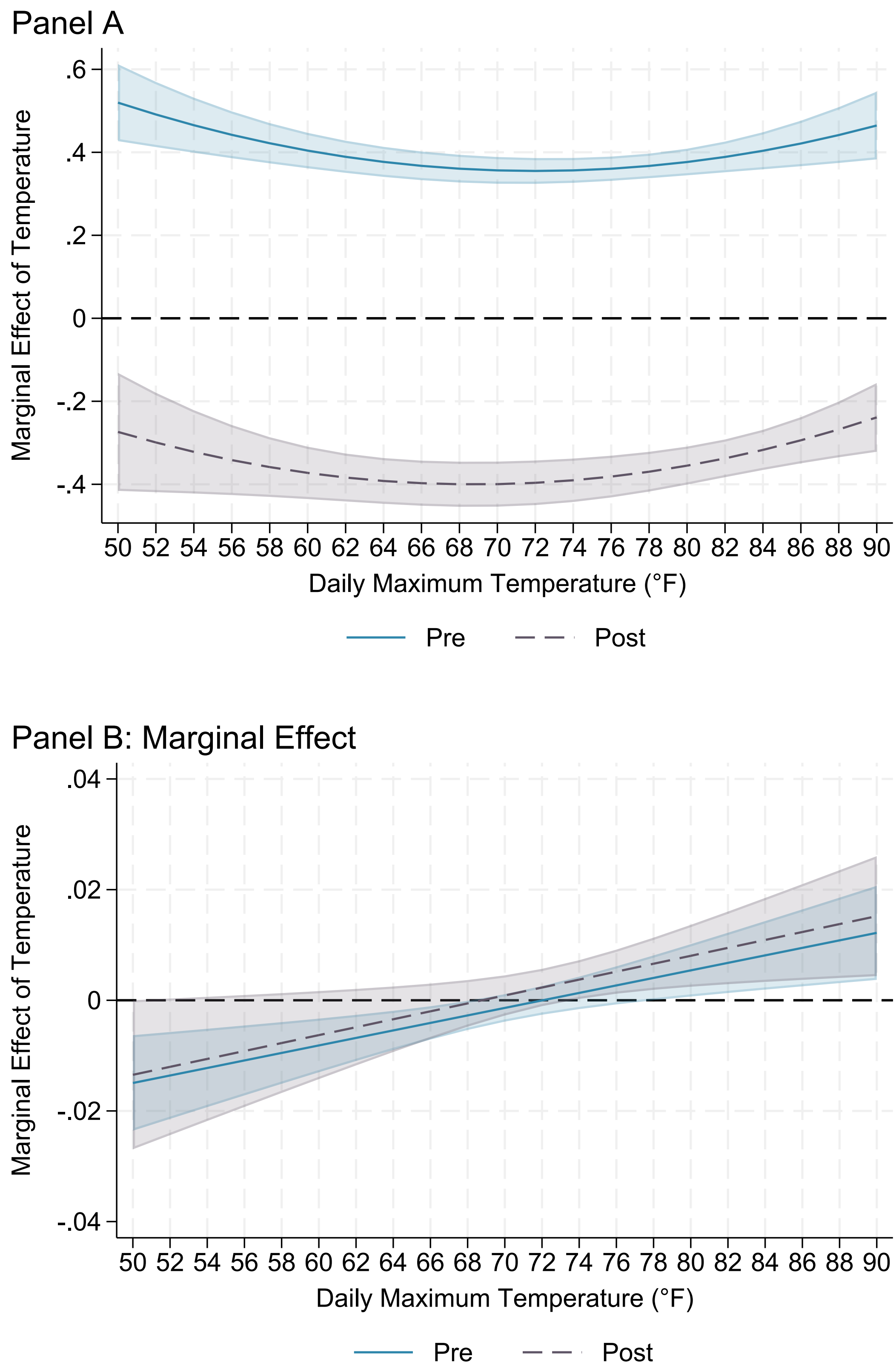

Figure 7: 2020 Shock

Notes: Estimated coefficients for the effect of temperature on athlete performance separated by race type and time period. Shaded regions denote 95% confidence intervals. The outcome mean is 0.101.

7 Conclusion

This paper uses NCAA Division I distance running to test whether incentive structure shapes performance responses to heat. Athletes run roughly one-fifth of a standard deviation slower in championship races than in regular-season races, consistent with a shift from time-maximizing to placement-focused racing under relative incentives. Athletes also run slower on hot days. But the magnitude of the heat effect is statistically indistinguishable across race types, and two parallel shocks in 2020 that increased uncertainty around qualifying thresholds — and narrowed the championship-versus-regular-season performance gap — did not alter heat responses. Together, these results indicate that temperature affects performance primarily through physiological rather than behavioral channels.

The setting we study is athletic, but the trade-off is general. Managers designing compensation schemes, teachers developing grading rubrics, and policymakers setting performance goals such as emissions or productivity targets all face the choice between absolute and relative metrics. Our results suggest that the standard considerations bearing on this choice — monitoring costs, risk preferences, scope for cooperation — are unlikely to be substantially reshaped by environmental shocks that affect all participants similarly. Whatever the optimal incentive structure for a given workplace or institution, that choice need not be revisited when conditions become hotter.

The implication for climate-adaptation policy is more pointed. A growing literature documents that heat reduces productivity across a wide range of settings, and a natural question is whether some of this loss can be recouped through incentive design — for example, by sharpening pay-for-performance when conditions become more difficult. Our findings caution against this hope. In our setting, where stakes are high and effort is closely monitored, athletes do not appear to adjust effort in response to heat in ways that incentive structure can shift. The losses appear physiological, and meaningful adaptation will need to come through investments that lower exposure — cooling, scheduling, infrastructure — rather than through redesign of how performance is rewarded.

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Online Appendix

"Do Incentives Shape Responses to Heat? Evidence from Track and Field"

Andrew Ireland Clayson Shumway

Round	Meet	Athletes	Heats	Q per heat	q
1500					
First Round	Regional Preliminary	96	8	5	8
Quarterfinal	Regional Preliminary	48	4	5	4
Semifinal	National Championship	24	2	5	2
3000 Steeplechase					
Quarterfinal	Regional Preliminary	96	6	3	6
Semifinal	National Championship	24	2	5	2
5000					
Semifinal	Regional Preliminary	96	4	5	4
10000					
Semifinal	Regional Preliminary	96	2	0	12

Table A.1: Qualifying Process

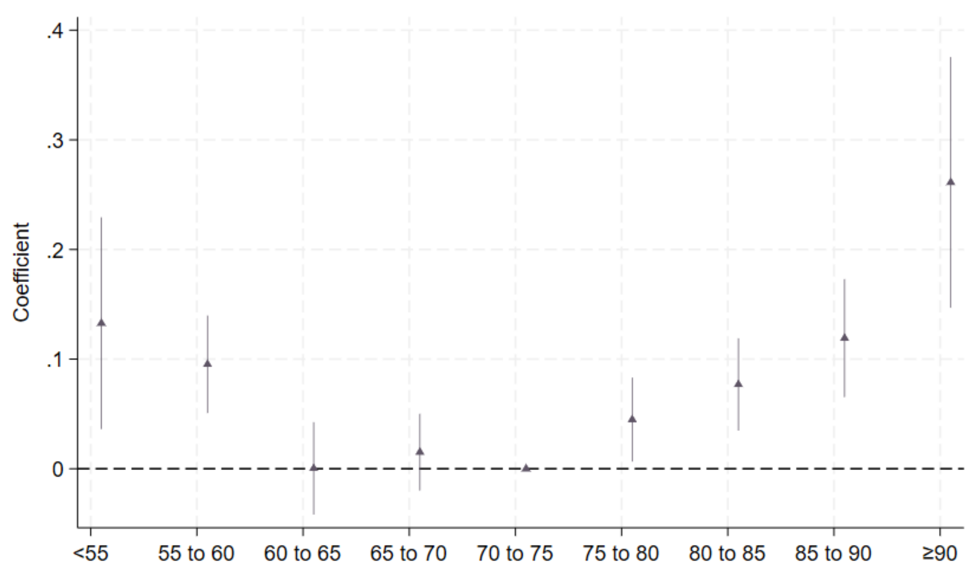

Figure A.1: Effect of Temperature - All Athletes

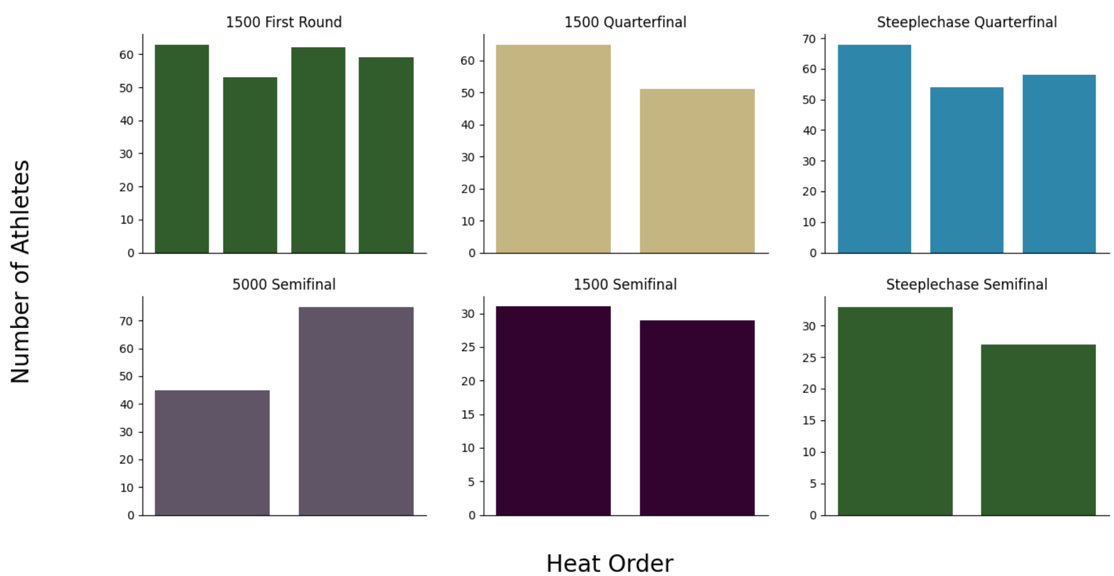

Figure A.2: Qualifying Time Trends

Notes: Histogram depicting the distribution of time qualifiers by round and event. The farther along the x-axis a bar occurs, the later that heat takes place. The height of each bar denotes how many athletes advance on time out of each heat in the order.