WINTER TEMPERATURE & DISTANCE RUNNING PERFORMANCE

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Introduction

Is there a relationship between winter temperatures and long-distance running performances? This paper will test the hypothesis that colder winters are negatively related to long-distance running performances during the indoor (winter) and outdoor (spring) track seasons. This hypothesis focuses exclusively on temperature variation within a region, not on if predominantly colder regions tend to perform worse.

Colder conditions make it more difficult for endurance athletes to breath and to warm-up their muscles. Both tasks are necessary to properly execute essential speed workouts. Additionally, frigid weather tends to have a detrimental impact on runners' motivation and enjoyment. Therefore, the conjecture that colder winters have adverse effects on distance runners' times is a reasonable hypothesis to evaluate.

In the process of investigating my hypothesis, I will also aim to answer the following questions: Does temperature have a different impact on college athletes compared to high school athletes? Do temperatures' effects vary by gender? Do colder winters have more of an impact on the indoor (winter) season or the outdoor (spring season)? Does snowfall have significant effects on running times?

This analysis is important because qualification for many of the U.S.'s most distinguished competitions (Ex: State Championships, NCAA Championships, Olympic Trials) are based on descending order lists. Since an athlete's ranking is affected by their competitors' performances, it is difficult for coaches to predict a time that will safely qualify their runners for important meets. As a result, elite runners frequently waste time, money, and energy trying to unnecessarily lower their times. Likewise, many unlucky athletes have lost chances to compete in championships by mistakenly thinking their spot was secure. This project may provide coaches and athletes with tools to improve their accuracy in predicting competitors' times which will allow them to more effectively plan their competition schedule.

There is little existing literature on weather and running performance. Runner's World Magazine (Mateo, 2019) recently published an article which discussed how cold temperature on race day hurts performance. Likewise, Peak Performance published a piece about winter running and increased risk of cardiovascular problems. However, literature using actual data to focus specifically on winter weather's effects on race performance later in the year is rare if not unavailable, making this study unique and informative.

My analysis will rely on a case study of high school and college track athletes living in New York (NY) and Pennsylvania (PA). I will assemble times ranked in the top fifty for men's and women's long-distance events for each year (2010-2020), in each state, at the high school and college levels. I will also calculate average winter (December, January, February) temperatures and snowfall for both states from 2010-2020. I will analyze the data with a series of linear regressions of performance on temperature controlling for year, state, snow, and gender. I will also capture the non-linear effect of temperature by running a quadratic regression and by grouping temperatures into different categories.

The results of this analysis support the hypothesis that colder winters have a negative impact on distance running performances during the winter and spring seasons. However, more studies should be conducted which use larger datasets, account for more relevant variables, and analyze performances in different types of races such as the mile (mid-distance) run.

Data Sources

I gathered time data form *Milesplit* (*milesplit.com*), the nation's premier venue for track and field results. *Milesplit* was the most appropriate source to use for three main reasons: 1.) Whereas other websites allow hand-timed results to be uploaded, *Milesplit* relies completely on Fully Automatic Time (FAT) which is much more accurate. 2.) In addition to providing national rankings, *Milesplit* also lists performances for every state, which makes the observations applicable to this paper's case study of New York and Pennsylvania. 3.) The database does not just provide top performances; it also lists many thousands of performances for every event for every state, making it a sufficiently large dataset to use.

I found temperature and weather information for New York and Pennsylvania using *weather.gov*. For New York, the website provided average Central Park temperature and snowfall for every month from 1869 until the present. For simplicity, I measured winter temperature as being the average temperature for the three coldest months (December, January, February). I made the assumption that Central Park weather conditions were the same as those in the rest of New York. This is a reasonable assumption because New York City is the most densely populated part of New York. Therefore, it is representative of the population of interest since a high percentage of New York's high schools and colleges are located in or near the City. For Pennsylvania, *weather.com* gives average weather for Philadelphia. Similar to New York, I make the assumption that winter weather in Philadelphia is consistent with that of all Pennsylvania. This assumption is also reasonable because Philadelphia is the most densely populated part of Pennsylvania. The temperature information was listed by month, so I found the mean of December, January, and February temperatures as I did with the New York data. By contrast, the snowfall data for PA was listed by year, not month, so it also included November and March snowfall. Therefore, my analysis may over-estimate snowfall in PA and underestimate it in NY. However, because large amounts of snowfall in November or March is rare, it will likely not bias this paper's conclusions.

Methodology

My analysis relies on a case study of high school and college track athletes living in New York and Pennsylvania. Using *Milesplit*, I compiled the top fifty men's and women's times in long-distance events for each year (2010-2020), for both states, at the high school and college levels.

I chose to focus on New York and Pennsylvania for a variety of reasons: For starters, both states are representative of the larger population of U.S. track athletes. New York has the second-most Division 1 athletics programs in the United States, and Pennsylvania ranks number 4 (state.1keydata.com). Similarly, both states are hubs for high school distance running, and frequently host some of the country's best competitions. Moreover, both states are subject to cold winters with below-freezing temperatures, making them appropriate test-cases for this study. Furthermore, both states have very similar winter weather. This allowed me to group the observations together and create a larger dataset for my regression. Since the project focuses on variation of temperature within a given region, it was a challenge to find a sufficiently large dataset, making the ability to group data together very useful.

Because this study aimed to determine if winter temperatures have a greater effect on the indoor track season (January, February, March) compared to the outdoor season (March., April, May), it was necessary to assemble data for both seasons, and to then run separate regressions for each. For both the indoor and outdoor seasons, I also had to run separate regressions for high school and college, since during the outdoor season the two age groups compete in different events that are not comparable. Because the hypothesis pertains to long-distance running, I analyzed the longest events I could find accurate data for. These events were: The 3,000 meter run (3k) for the high school indoor season, the 3200 meter run (3200m) for the high school outdoor season, the 3,000 (3k) meter run for the college indoor season, and the 5,000 (5k) meter run for the high school outdoor season. For some events, such as the girls high school 3200m, I had to convert times from the 3k to the 3200m since NY and PA race slightly different distances.

For each of the four events, I compiled the top 50 times run by males and by females, in each state, for every year from 2010-2019. Data from the indoor season was available for 2020, but not for the outdoor season since it was cancelled due to the Covid-19 virus. In total, 8800 times were included in the study. I chose to collect data on top performers instead of average ones because this study focuses on how elite runners can gain a competitive edge in their meet-preparation.

Once I had collected all the weather and time information, I matched the two datasets together so that each performance would correspond to an average winter temperature. I ran linear regressions for each event controlling for year, state, snow, and gender. I had to control for a time-trend (year) because I suspected that, on average, performances would improve each year as factors such as nutrition tended to improve. Likewise, it was necessary to account for state because I suspected that, on average, NY's times would be faster PA's since New York is home to some of the finest indoor facilities in the country. Similarly, it was of the utmost importance to control for snowfall because otherwise my estimates would have suffered from the omitted variable bias. This is because snowfall is likely correlated with temperature and performance. I also had to control for gender because, on average, men's times tend to be faster than women's.

After running linear regressions for each event/season, I dropped outliers and reexamined the linear relationship. Instead of using an outlier formula, I deemed an observation an outlier if the time was ranked top ten in the U.S. I also re-ran the linear regressions separately for each gender.

It was also important to capture any non-linear effects of temperature on performance. As a result, I chose to create a temperature-squared term to investigate a potential quadratic relationship. Additionally, I grouped temperature into ranges (Cold, Mild, Warm) and ran a regression using dummy variables for each category. The minimum temperature in the sample was 31.43 degrees, and the maximum was 41 degrees. So, to distinguish between the three categories, I created the following ranges/dummies: Cold (31.43-34.61); Mild (34.62-37.80); Warm (37.81-41).

It is important to note that this analysis relies on time-series data. Typically, to obtain unbiased estimates with time-series data it is necessary to account for all cross-sectional variation among individuals using methods such as the fixed effects model. However, important individual characteristics such as years of experience and income levels were unavailable. So, this study rests on the assumption that enough relevant individual differences have been accounted for to produce unbiased results. Though this is a simplifying assumption, it is a reasonable one. Gender and state, which are likely the most important individual characteristics, were controlled for. Additionally, because distance runners tend to have much in common such as similar body types and personalities, it is likely that, on average, there is little variation among individuals after controlling for gender and state.

Findings

Summary Statistics

To provide readers with background necessary to understand the results of my analysis, I've included key summary statistics tables below. To avoid overburdening readers, for the time variable I list only the summary statistics for the college 5k (outdoor season). However, time variable tables for the other three events can be found in the appendix. As shown in table 1, mean winter temperature for the sample was 36.58 °F, and mean snowfall was 30.38 inches. Average winter temperatures in PA and NY were only .45 degrees apart, making it simple to group their observations together. Average snowfalls differed slightly more, with PA receiving 10 inches more per year on average. As table 2 illustrates, the average 5k time for a college male ranked in the top 50 of their state was 872.48 seconds (14:32.48). For females, the average top-fifty ranking time was 1,034.74 seconds (17:14.74). As suspected, times in New York were 2.69 seconds faster on average than times in Pennsylvania. For all four events, men ran faster times than women, and New Yorkers ran faster times than Pennsylvanians.

Table 1: Summary Statistics

Variable	Obs.	Mean	S.D.	Min.	Max.
Temp.	1,050	36.58	3.17	31.43	41
Temp. (PA)	550	36.78	3.05	32.75	4094
Temp. (NY)	550	36.33096	3.307996	31.43	41
Snow	950	30.38	22.84478	3.7	78.7
Snow (PA)	450	35.98	24.82453	4	78.7
Snow (NY)	500	25.34	19.60082	3.7	60.9
State	1,100	.45	.498	0	1
Year	1,100	2015.002	3.17	2010	2020
Gender	1,100	1	0	1	1
Temp_Cat	1,100	.818	.389	0	1

Table 2: College 5k (Outdoor Season)

Variables	Observations	Mean	Standard Deviation	Min	Max
Time (Males)	1,000	872.48	17.75	798	907
Time(Females)	1,000	1034.74	32.33	924	110
Time(PA)	1,000	954.9	83.72	806	1082
Time (NY)	1,000	952.21	86.71	798	1110

Linear Regressions

Tables 3-6 (found below) portray the results of the linear regressions. Related graphs and figures can be found in the appendix. Discussion of the results will focus first on the first three events (tables 3-5): the college outdoor 5k, college indoor 3k, and high school outdoor 3200m. Then, it will analyze the results for the high school indoor 3k. Column one represents the results of the overall regression which includes both genders together. Column two depicts the results of the same regression after outliers have been removed. Column three shows the results focusing exclusively on males' performances, and column four represents the same but for females.

Table 3: College Outdoor (5k)

	Overall	No outliers	Men	Women
temp	-0.582*	-0.594*	0.0390	-1.214**
	(0.245)	(0.239)	(0.228)	(0.414)
snow	0.00486	0.00771	0.0532	-0.0365
	(0.0381)	(0.0377)	(0.0355)	(0.0662)
state_	-2.547*	-2.404	-3.671**	-1.140
	(1.261)	(1.246)	(1.138)	(2.203)
gender	163.5***	162.8***		
	(1.217)	(1.201)		
year	-1.190***	-1.135***	-0.796***	1.470**
	(0.260)	(0.258)	(0.239)	(0.453)
_cons	3290.9***	3181.4***	2475.0***	4042.2***
	(523.8)	(519.3)	(481.6)	(913.9)
N	1799	1789	890	899
r2	0.910	0.911	0.0465	0.0334

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 4: High School Outdoor (3200m)

	Overall	No Outliers	Men	Women
temp	-0.280*	-0.295*	-0.0396	-0.540*
	(0.128)	(0.127)	(0.122)	(0.221)
snow	0.0134	0.0123	0.0415*	-0.0160
	(0.0211)	(0.0210)	(0.0199)	(0.0370)
state_	-5.241***	-5.253***	-4.924***	5.437***
	(0.663)	(0.660)	(0.639)	(1.199)
gender	93.61***	93.50***		
	(0.639)	(0.637)		
year	-0.235	-0.224	-0.0952	-0.351
	(0.130)	(0.130)	(0.131)	(0.233)
_cons	987.1***	965.5***	696.0**	1325.9**
	(262.7)	(262.4)	(263.3)	(469.2)
N	1800	1797	897	900
r2	0.924	0.924	0.0874	0.0438

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 5: College Indoor (3k)

	Overall	No Outliers	Boys	Girls
temp	-0.305*	-0.308*	-0.0204	- 0.590**
	(0.125)	(0.123)	(0.146)	(0.189)
snow	-0.0217	-0.0210	0.00935	-0.0506
	(0.0193)	(0.0191)	(0.0217)	(0.0305)
state_	-5.718***	-5.597***	-1.772*	9.404***
	(0.623)	(0.621)	(0.704)	(1.003)
gender	93.74***	93.59***		
	(0.598)	(0.595)		
year	-0.174	-0.160	-0.0214	-0.296
	(0.127)	(0.126)	(0.135)	(0.211)
_cons	927.1***	899.0***	607.0*	1279.7**
	(255.4)	(255.1)	(271.2)	(425.1)
N	1800	1796	896	900
r2	0.932	0.933	0.00916	0.0998

Table 6: High School Indoor (3k)

	Overall	No Outliers	boys	girls
temp	-0.125	-0.125	-0.0813	-0.174
	(0.141)	(0.140)	(0.138)	(0.233)
snow	0.0277	0.0280	0.00443	0.0511
	(0.0233)	(0.0233)	(0.0225)	(0.0391)
state_	-16.76***	-16.80***	-9.543***	-24.05***
	(0.778)	(0.776)	(0.759)	(1.306)
gender	89.43***	89.34***		
	(0.725)	(0.722)		
year	-0.175	-0.163	-0.212	-0.115
	(0.155)	(0.154)	(0.146)	(0.261)
_cons	903.2**	878.0**	972.6***	875.5
	(312.3)	(311.7)	(294.2)	(525.9)
N	1800	1798	898	900
r2	0.898	0.898	0.180	0.309

Confirming Evidence

For the first three events, colder temperatures had a statistically significant, negative relationship with performance at the 95% confidence level. In the 5k run, a 1°F increase in temperature was associated with a .582 second improvement in time. For the 3k and 3200m events, the magnitude of its impact was slightly less at .28 and .305, which was consistent with my initial predictions since those events are shorter. Removing outliers had a minimal impact on results. Surprisingly temperature drops were more negatively correlated with female achievement than with male achievement. For all three events, the magnitude of temperature's coefficient increased once male observations were dropped from the dataset. Moreover, for the college and high school outdoor seasons, this coefficient became statistically significant at the 99% confidence level. These results go against my initial expectations that gender would not be an important factor. One possible explanation is that female endurance athletes tend to run lower mileage but at a higher intensity. Cold weather should have more of a negative impact on high-intensity training which relies more on quick-twitch movements.

As I predicted, performances exhibited a significant time trend. For the college 5k, moving from one year to the next was associated with 1.19 second improvement in time on average. This coefficient was significant at the 99.9% confidence level.

Counter to my prediction, snowfall was not significantly correlated with performance. However, for three out of the four events, the coefficient on snow was positive, indicating that as snowfall increased, times rose (worsened). This is consistent with my expectations. There are a couple of explanations for these results: One is that snow does have a negative impact on performance, but my sample size is not large enough for my analysis to yield statistically significant results. Another is that snow does not affect performance. After a storm, roads are usually plowed in time to allow endurance athletes to continue their training. Likewise, most colleges have access to indoor facilities and high schools often shovel their tracks. Investigating snows impact on athletic achievement should be an important focus of future studies.

Another surprising result of my regression analysis was that temperature had about the same impact on both the indoor and outdoor seasons. Indoor meets occur in the winter, directly in the midst of the colder months. As a result, frigid temperatures may be a detriment to athletes' training during the days immediately leading up to the competition. By contrast, the outdoor season occurs in the spring, with most important competitions scheduled months after any unfavorably cold weather. The results of the regressions support the notion that the effects of training are delayed, so what an athlete does to prepare months before a competition is just as important as what they do immediately prior to a competition.

Additionally, temperature's effect on high school athletes' performances was about the same as its effect on college athletes'. The coefficient on temperature was negative and statistically significant at the 95% confidence level for both the high school and college outdoor seasons. Though the magnitude was greater for the college outdoor season, this likely reflects the longer distance run by college athletes (5k vs. 3200m).

Counter Evidence

Results of the linear regression based on the high school indoor season provide evidence against my hypothesis. As table six illustrates, the coefficient on temperature is still negative, but is not statistically significant. This lack of significance brings the validity of my hypothesis into question. However, the results must be regarded with caution because the data exhibits some unusual characteristics. According to *Milesplit,* over the last decade NY's high school runners have averaged times that were 16 seconds faster than PA's in the indoor 3k. Such a considerable difference in times is exceptional rare. If NY had a few uncharacteristically fast years in the indoor 3k, this could likely bias the results. It is also possible that *Milesplit* made an error in its reporting one of the years. Unfortunately, since *Milesplit* is the only site that conducts this sort of data gathering, there is no way to check. What I conclude is that this regression for the high school indoor season does offer some counter-evidence against my hypothesis, but should be regarded with moderate caution.

Examining Non-Linear Relationships

To capture the non-linear effect of temperature, I created a temperature-squared term. Results of the quadratic regression can be found in table 7 below. Temperature had a statistically significant quadratic relationship with performance for both the college and high school outdoor seasons. However, the direction of the association differed. For college outdoors (figure 8), as temperature increased, times fell but at a decreasing rate. For high school outdoors (figure 9), times initially rose as temperature increased, but at a decreasing rate. Then, if temperatures exceeded 35 degrees, times began to fall at an increasing rate. These results indicate that colder temperatures actually have more of a negative impact on college runners than on high school runners. Additionally, they support the claim that the negative impact of cold weather is delayed until the later outdoor season. This could be because gains from training often do not come into fruition until months later during an athlete's peak phase.

Using another method to capture temperature's non-linear effects, I grouped temperature into three different categories: cold, mild, and warm; and ran a regression using the categories as dummy variables. Results can be found in table 10. For three out of the four events, category dummies were significantly, positively related to performance. Temperature had a greater positive impact on performance when it was within the mild category than when it rose to the warm category. Both non-linear analyses indicate that temperature increases may better performance, but it exhibits diminishing marginal returns.

Table 7: Quadratic Relationship All Events

	College Outdoor	HS Outdoor	College Indoor	HS Indoor
temp	-18.84**	6.159*	0.356	-5.014
	(6.554)	(3.127)	(3.561)	(3.419)
Temp^2	0.249**	-0.0880*	-0.00865	0.0678
	(0.0889)	(0.0426)	(0.0481)	(0.0468)
snow	-0.00561	-0.0180	0.0137	0.0299
	(0.0384)	(0.0193)	(0.0215)	(0.0234)
state_	-2.402	-5.769***	-5.242***	-15.70***
	(1.262)	(0.623)	(0.663)	(0.782)
gendr	163.5***	93.74***	93.61***	88.56***
	(1.215)	(0.598)	(0.640)	(0.734)
year	-1.151***	-0.188	-0.236	0.0350
	(0.261)	(0.127)	(0.131)	(0.161)
_cons	3544.9***	838.2**	978.6***	566.5
	(525.4)	(260.6)	(263.4)	(324.8)
N	1799	1800	1800	1800
r2	0.910	0.932	0.924	0.894

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 10: Category Dummy Regression

	College Outdoor	HS Outdoor	College Indoor	HS Indoor
mild	-6.725*	1.776	-3.237**	-2.483*
	(2.821)	(1.360)	(1.104)	(1.214)
warm	-2.664*	-0.944	-1.732***	-0.173
	(1.093)	(0.546)	(0.444)	(0.521)
snow	-0.0270	-0.0102	-0.0146	0.0243
	(0.0457)	(0.0229)	(0.0212)	(0.0242)
state_	-1.599	-6.309***	-4.885***	-15.22***
	(1.353)	(0.656)	(0.698)	(0.792)
gender	163.5***	93.74***	93.66***	87.66***
	(1.217)	(0.597)	(0.624)	(0.712)
year	-0.957***	-0.257	-0.0440	0.0936
	(0.281)	(0.134)	(0.125)	(0.150)
_cons	2804.7***	1085.0***	595.2*	357.4
	(566.1)	(268.8)	(251.4)	(302.7)
N	1799	1800	1900	1900
r2	0.910	0.932	0.923	0.892

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Figure 8: College Outdoors

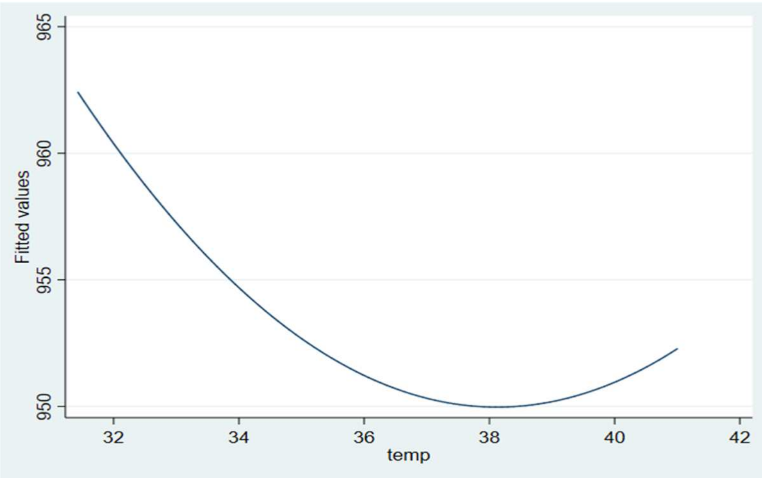
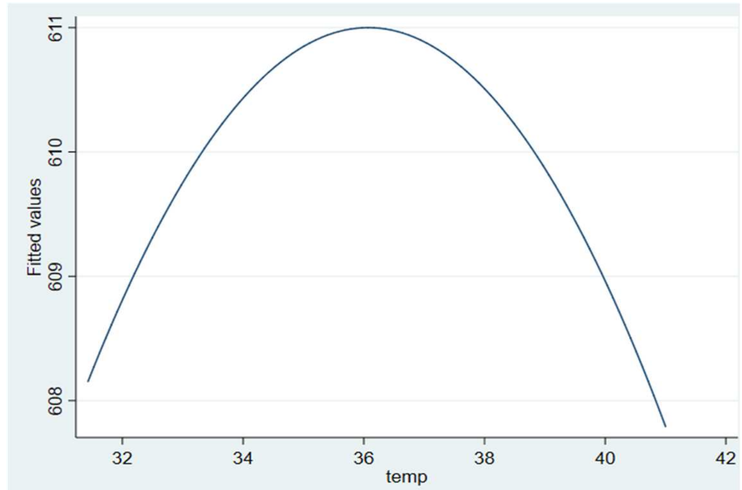


Figure 9: High School Outdoors



Conclusion

There is sufficient evidence to conclude that colder winters are negatively related to long-distance running performances during the indoor and outdoor track seasons. For three out of the four events analyzed, linear regressions of performance on temperature yielded negative coefficients that were statistically significant at the 95% confidence level. In other words, a temperature increase was associated with a significant improvement (drop) in time. Non-linear analyses also provide evidence in favor of my hypothesis. For two out of the four events (college outdoors and high school outdoors), temperature had a statistically significant quadratic relationship with performance. For college runners, increases in temperature were associated with an immediate improvement in performance. For high school runners, initial increases in temperature were negatively related to performance at first, but after reaching the threshold of 35 degrees, it began to have a positive impact on achievement. Running a regression with dummy temperature-range variables also yielded significantly significant results which indicated that times tended to improve as temperature increased, but at a decreasing rate.

This analysis also presented other useful findings: Females' performances are hurt more by colder weather than males'; snowfall does not have a significant impact on performance; high school and college athletes are impacted the same by harsher weather; and colder weather impacts results of the indoor and outdoor seasons equally.

There are potential improvements that would make future studies in this area even more accurate. This project relied on a large sample of performances, but because of the nature of the data, only a very small sample of twenty temperature variations was available. More weather data would improve the accuracy of future analyses. Additionally, this paper focuses only on the longest-distance events. Analysis of slightly shorter races such as the mile run would make the study more nuanced. Also, because of the unavailability of certain data, estimates may suffer slightly from the omitted variable bias. For instance, spring weather is likely correlated with winter weather and running achievement, but was not included in this project. Likewise, as aforementioned, limited data left me unable to account for all cross-sectional variation between individuals. However, because I have accounted for the most relevant factors, and conducted many different kinds of analyses, my results are accurate enough to form reasonable conclusions.

There are important applications of this paper's conclusion that colder winters are associated with a drop in performance. Typically, coaches give their athletes a goal time to hit that will safely qualify them for big meets. If they hit the time, they usually refrain from racing until the championship. Now, with this analysis, coaches can modify their predictions based on the winter's average temperature. Doing so will increase make it easier for runners to achieving their dreams by qualifying for prestigious meets such as State Championships, the NCAA Championships, and the Olympic Trials.

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Appendix

High School 3200M (Outdoor Season)

Variables	Observations	Mean	Standard Deviation	Min	Max
Time (Males)	1,000	563.022	10.28	523	580
Time(Females)	1,000	656.29	15.64	590.53	684
Time(PA)	1,000	612.632	49.67	536	684
Time (NY)	1,000	606.69	47.13	523	675.36

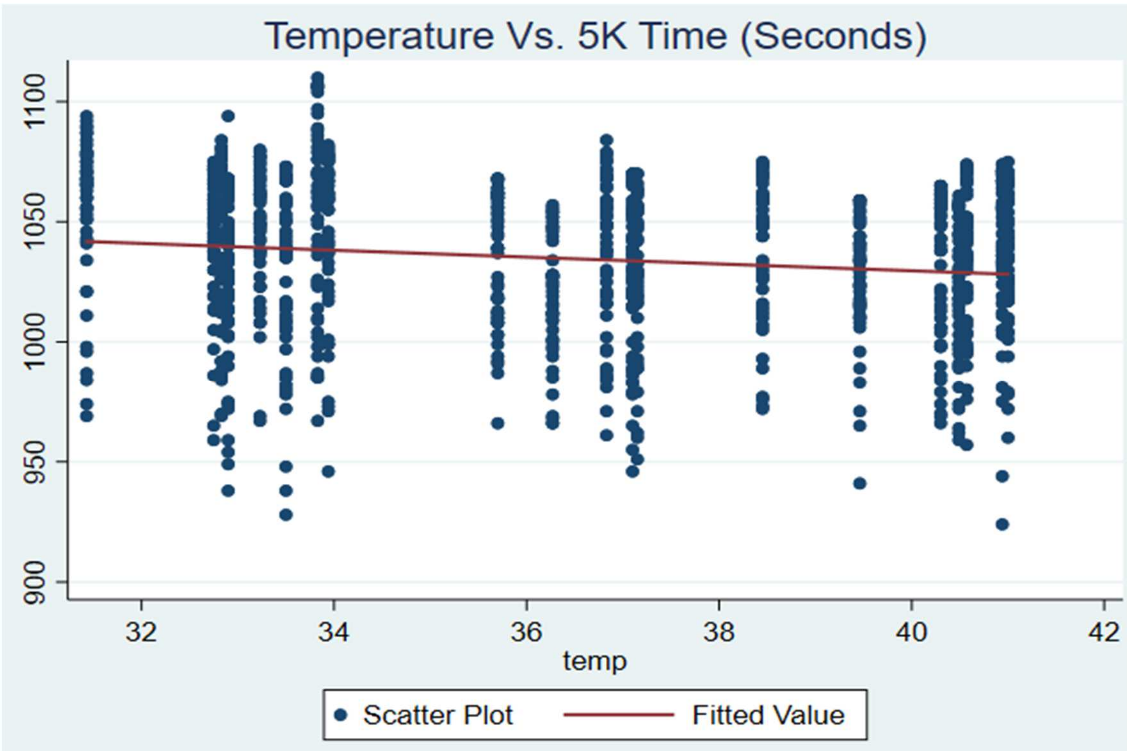
College 3K (Indoor Season)

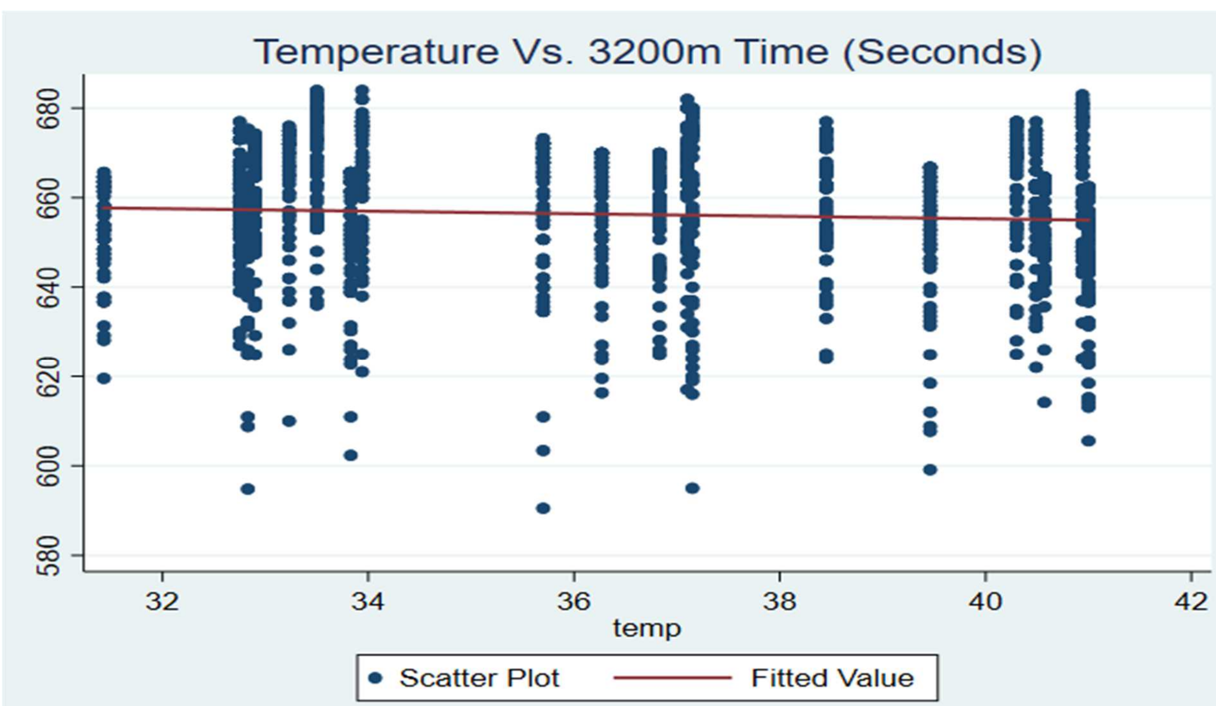
Variables	Observations	Mean	Standard Deviation	Min	Max
Time (Males)	1,100	502.23	9.87	468	521
Time(Females)	1,100	595.33	16.89	533	627
Time(PA)	1,100	553.19	48.31	469	627
Time (NY)	1,100	543.96	48.42	468	625

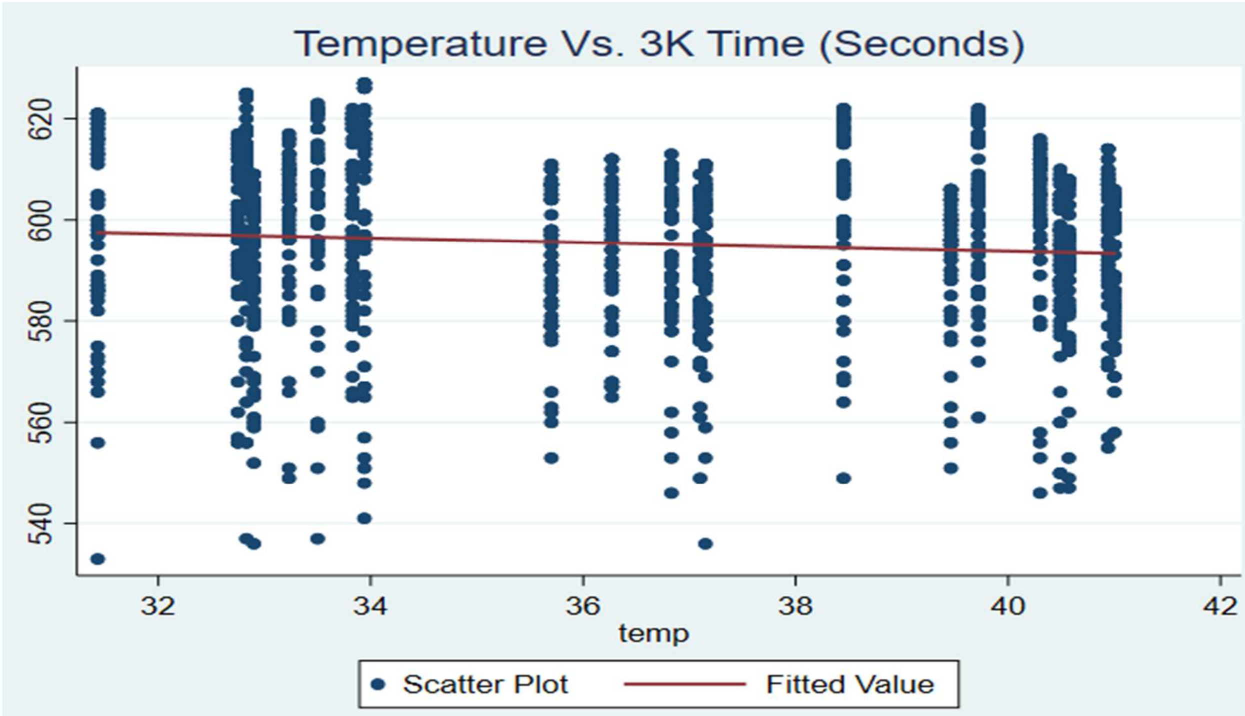
High School 3K (Indoor Season)

Variables	Observations	Mean	Standard Deviation	Min	Max
Time (Males)	1,100	538.194	11.77	497	566
Time(Females)	1,100	627.15	22.539	542	677

Time(PA)	1,100	591.98	50.42	497	677
Time (NY)	1,100	572.48	42.77	497.37	641






Temperature Vs. 3K Time (Seconds)
620
600
580
560
540
32
34
36
38
40
42
temp
Scatter Plot
Fitted Value