

# Using COVID-19 response policy to estimate open water and swim drafting effects in triathlon

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## ABSTRACT

This study investigates the causal effects of open-water swim drafting by leveraging a natural experiment induced by staggered race starts during the COVID-19 pandemic. Before 2020, athletes started in groups, enabling drafting benefits, while pandemic-related restrictions significantly reduced these opportunities. Using agglomerative hierarchical clustering of swim-out times, I analyze optimal drafting positions and estimate their impact on Swim-Out performance. Our empirical findings reveal that swim drafting benefits were statistically insignificant in 2020 but persisted post-pandemic at slightly reduced levels. I find that drafting becomes advantageous only from the third trailing position onward, with earlier positions primarily serving to minimize fatigue. To mitigate endogeneity, I employ athlete and event fixed effects. The seemingly inverse decaying nature of drafting benefits partially addresses some concerns of simultaneous reverse causality and omitted variable bias. This study provides the first largescale causal estimate of drafting effects in real-world triathlon race settings.

**Keywords:** Quasi-experimental design, Open water swimming, Drafting, COVID-19, Sports economics.

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## INTRODUCTION

Aerodynamics plays a significant role in everyday life, whether you own a car, book a flight, or race your neighbor in a cycling competition. In cycling, rotational overtaking maneuvers and shared drafting advantages have long been a common practice, both in racing and training. Similarly, in triathlon, the role of drafting is well recognized, leading to the existence of two distinct race formats:

1. Elite short- and middle-distance races, where wind-drafting is explicitly allowed, transforming these events into highly strategic competitions.
2. Long-distance and amateur triathlon races, where wind-drafting is strictly prohibited, and violations result in time penalties.

In these latter formats, the only real opportunity for drafting occurs in the swim segment, where swimmers can strategically position themselves to reduce drag. Swim drag reduction through drafting has been extensively studied in medical science, soft matter physics and sports science in Bolon et al. (2020); Chatard et al. (1990); Chatard and Wilson (2003); Ohmichi et al. (1983); Millet et al. (1999); Delextrat et al. (2003); Olbrecht (2011); Toussaint et al. (1989). However, no large-scale causal estimates of its benefits in real race settings have been published.

The COVID-19 pandemic introduced precautionary measures in Austria which significantly altered the swim segment dynamics. According to Österreichischer Triathlonverband (ÖTRV) Athletes often had to start with individually staggered swim entries, and overtaking at buoy turns was sometimes somewhat restricted. This created a natural experiment where COVID-19 functioned as an exogenous short-term shock (1–3 years) to open-water swim drafting, providing an opportunity to analyze its effects in a controlled manner.

In this paper, I employ agglomerative hierarchical clustering of swim-out times to infer likely swim group formations and estimate the optimal drafting positions within swim-groups in race settings. This is the first study to provide large-scale causal estimates for open-water drafting effects using panel data. Water drafting has long been a hot topic in both sports science and professional triathlon. With internet sources claiming that an athlete can gain up to between  $\approx 7\%-21\%$  on overall drag reduction, which results in a reduction of 2 minutes over a half-distance Ironman swim of 1,900m.<sup>1</sup>

Beyond race performance, other strategic considerations—such as energy conservation and positioning to catch the first cycling group in elite competitions where wind drafting is permitted—play a critical role.

### **Related literature**

Empirical research on open-water swim drafting has consistently demonstrated its benefits in terms of reduced drag, energy conservation (metabolic costs), and improved race performance.

#### *Hydrodynamic and physiological benefits of drafting*

Studies have shown that drafting significantly reduces drag and physiological strain. Bolon et al. (2020) determined that optimal drafting positions—directly behind a lead swimmer or at the hip—result in drag reductions of 40% and 30%, respectively. Chatard and Wilson (2003) found that metabolic costs, including oxygen uptake, heart rate, and blood lactate levels, were significantly lower when swimmers drafted at distances of 0 to 50 cm behind another swimmer's toes. The most advantageous drafting distances were 0

<sup>1</sup> Drafting in Triathlon: <https://support.myprocoach.net/hc/en-us/articles/360022528551-Drafting-in-Triathlon#:%3Atext=Swim%20Drafting,you%20up%20to%20two%20minutes>

and 50 cm, reducing passive drag by 21% and 20%, respectively. Additionally, Ohmichi et al. (1983) found that swimmers drafting directly behind another competitor completed 400-m races significantly faster than those who swam at the side or hip.

#### *Drafting and performance prediction*

The role of passive drag (Dp) in swim performance prediction was examined by Chatard et al. (1990), who found a strong correlation between Dp and  $VO_{2\max}$ . Performance times were primarily influenced by  $VO_{2\max}$  ( $r = 0.70$  for males,  $r = 0.72$  for females), but including Dp significantly improved the predictive accuracy. The strong correlation hints at the possibility that more able athletes might be more sensitive to properly utilizing passive drag. Other anthropometric factors, including height, weight, and body surface area, also contributed to drag variability. This athlete heterogeneity underscores the need to include athlete-specific intercepts or characteristics in predictive models. Millet et al. (1999) further emphasized the cumulative impact of drafting, showing that triathletes employ energy- conserving strategies in swimming to enhance their subsequent cycling and running performances.

#### *Tactical implications for triathletes*

Drafting has been shown to enhance subsequent cycling performance. Delestrat et al. (2003) reported a 4.8% improvement in cycling efficiency when a swim was performed in a drafting position compared to an isolated swim. Millet et al. (1999) also stated the cumulative effects of drafting in triathlon, where athletes strategically conserve energy in the swim segment to optimize performance in the cycle and run segment. Olbrecht (2011) thus underscores the importance of balancing conditioning and technique, arguing that poor swimming technique results in excessive energy expenditure, ultimately affecting overall race outcomes.

#### *Impact of equipment and external conditions*

The effect of wetsuits on swim drafting was investigated by Toussaint et al. (1989), who observed a 14% reduction in drag at typical triathlon swim speeds. This reduction, largely attributed to increased buoyancy and decreased frontal resistance, resulted in higher swim velocities. Moreover, Leitner (2021) conducted an athlete survey revealing preferences regarding mass starts versus staggered starts, highlighting the impact of the race format on drafting opportunities. An alternative survey on wetsuit use could further reveal preferences for drafting but is likely highly confounded by the swim- to-bike transitional race segment. The COVID-19 pandemic introduced natural experiments with staggered starts, as documented by Österreichischer Triathlonverband (ÖTRV), which temporarily altered swim drafting dynamics.

#### *Summary of existing literature*

The body of research highlights drafting as a critical factor in competitive swimming and triathlon. Hydrodynamic studies focus on reductions in drag, while physiological research conclude that drafting lowers metabolic costs. Performance predictions could therefore benefit from incorporating passive drag measures. External conditions, such as wetsuit use (unobservable, if allowed in an event and race format subject to race organizers and race regulation authorities), technological wetsuit evolution and innovative race formats (such as the 'Super Sprint' e.g.) or short-term race format shocks (such as the COVID-19 pandemic), further influence drafting effectiveness.

## **MATERIALS AND METHODS**

The dataset originates from three relational database tables provided by the Triathlon Statistics Austria database, covering most official triathlon races that took place in Austria from 2010 to 2024. Initially, the

dataset contained 175,740 recorded observations. After removing DNF (Did Not Finish) and DNS (Did Not Start) outcomes, as well as missing data, I obtained a final dataset of 168,391 observations.

### **Dataset structure**

The dataset is structured into three relational tables:

- Athlete(a): Contains athlete-specific details.
- Events(e, t): Represents official triathlon events e over time t.
- Result(r, a, e, t): Stores results r of each athlete a in specific events e captured at time t.

### **Preprocessing and period definitions**

The dataset was processed by first merging the result table with the events and athlete table using foreign keys. Events were then assigned to one of three periods based on their date, resulting in three binary dummy variables. Additionally, event-time-variant covariates such as age or squared age were computed in the final dataset as  $age_{a,t} := year_{(t)} - year_a$ , which were then additionally used as a distributional covariate balance check across periods.

### **Construction of swim groups**

To analyze drafting effects, swimmers were clustered based on their swim-out time within an event. A hierarchical clustering algorithm was applied with a 5-second threshold for forming swim groups. It is noted that in the initial model trials, clustering was also performed using the complete link- age method with an increased cutoff threshold of 15 seconds before finalizing the single linkage approach. The clustering procedure involved calculating the time difference between athletes in an event and grouping them based on proximity. A single linkage method was used, ensuring that swimmers within 5 seconds of each other were assigned to the same swim group. Each cluster was assigned a leader, defined as the athlete with the fastest swim-out time. All other athletes in the group were designated as drafters. Within the drafting group, individual positions were encoded, categorizing athletes as first, second, third, fourth, fifth, and/or last drafters based on their relative swim-out times.

### **Summary statistics**

Table 1. Summary statistics of numerical variables.

Variable	Min	1st Quartile	Median	Mean	3rd Quartile	Max
Total	165	4965	8232	11789	16809	61282
Swim-Out times	4	825	1431	1625	2097	29700
Race rank	0	28	69	156.9	151	2623
Male	0.0000	1.0000	1.0000	0.7898	1.0000	1.0000
Year	1922	1969	1977	1977	1985	2009
COVID	0.0000	0.0000	0.0000	0.1097	0.0000	1.0000
Post COVID	0.00000	0.00000	0.00000	0.08563	0.00000	1.00000
Week running	0.0	159.0	279.0	317.6	475.0	751.0
Age	8.00	31.00	38.00	38.56	46.00	99.00
Age squared	64	961	1444	1600	2116	9801
Event year	2010	2013	2015	2016	2019	2024
Cluster (swim group)	1.00	4.00	10.00	16.95	23.00	224.00
Leader	0.0000	0.0000	0.0000	0.3134	1.0000	1.0000
Drafter	0.0000	0.0000	1.0000	0.6866	1.0000	1.0000
Drafter position	1.00	1.00	3.00	17.15	11.00	937.00
First drafter	0.0000	0.0000	0.0000	0.2961	1.0000	1.0000
Second drafter	0.0000	0.0000	0.0000	0.1342	0.0000	1.0000

Third drafter	0.00000	0.00000	0.00000	0.08329	0.00000	1.00000
Fourth drafter	0.00000	0.00000	0.00000	0.05846	0.00000	1.00000
Fifth drafter	0.000	0.000	0.000	0.044	0.000	1.000
Last drafter	0.0000	0.0000	0.0000	0.2961	1.0000	1.0000

Notes: This table presents summary statistics for the key variables used in the analysis. The dataset consists of 168,391 observations. Variables include athlete characteristics, race details, and encoded swim group (cluster), drafting, drafting position binary dummy variables. Encoded categorical variables such as Event Category  $\in \{\text{Sprint, Short, Middle, Long}\}$  are not displayed.

### Balance checks

To ensure comparability (e.g. problems with the panel data such as attrition) across event categories and periods, some descriptive and visual balance checks on key event, result and athlete variables were performed.

### Swim-out times across event category and period balance

Swim-out times were analyzed across different event categories (Sprint, Short, Middle, and Long) and periods (Pre-COVID, COVID, and Post-COVID) to assess differences. The results indicate slight increases in mean swim-out times post-COVID for most Sprint and Short events. This trend however was expected, as the movement towards more accurate swim distances and longer swim distances in the Short category over the last decade is well known among Austrian triathlon insiders. The balance check is shown in Table 2.

### Athlete characteristics across periods

Athlete-level characteristics, including mean swim-out time, rank, age, and the proportion of male participants, were examined to assess balance across periods. Age distribution trends indicate a slight increase in the average age of athletes since the pre-COVID period starting in 2010, alongside a slight decline in the overall high proportion of male participants. Additionally, the observed decrease in mean rank suggests a shift in event market structure, potentially favoring a higher number of smaller events or fewer mass events. However, this trend could also be entirely driven by an outlier event within the longer period spanning 2010 to 2019.

Table 2. Results (swim-out times) across different event categories and periods.

Event category	Period	Mean swim-out time	SD swim-out time	Observations
Short	COVID	1855	380	4694
Short	Post-COVID	1899	403	3726
Short	Pre-COVID	1696	415	37722
Long	COVID	4594	804	1130
Long	Post-COVID	4572	1035	1014
Long	Pre-COVID	4553	773	10201
Middle	COVID	2311	380	4658
Middle	Post-COVID	2315	394	3527
Middle	Pre-COVID	2216	436	26711
Sprint	COVID	854	295	7985
Sprint	Post-COVID	906	296	6152
Sprint	Pre-COVID	774	258	60871

### Identification strategy

#### Event-Induced altered drafting opportunity

This study leverages the staggered race starts implemented during the COVID-19 pandemic to estimate the magnitude of drafting benefits in open-water swimming. Before 2020, athletes started in groups, allowing

drafting effects to influence race performance. However, during the pandemic, individually staggered starts significantly reduced drafting opportunities. This natural experiment offers a unique opportunity to assess drafting's impact by comparing race outcomes before, during, and after the pandemic.

#### *Confoundedness, effect heterogeneity and higher-order drafting position effects*

To formally identify the effects of drafting, I estimate the impact of drafting and within-swim-group position on Swim-Out times, using likely constructed swim groups based on clustered Swim-Out times. Furthermore, I employ athlete and event fixed effects to control for unobservable heterogeneity and to partially address some endogeneity concerns such as omitted variable bias and simultaneous reverse causality. The positioning within a swim group likely affects the magnitude of drafting benefits, with higher-order positions benefiting more from overall reduced water resistance (increased passive drag), leading to varying performance outcomes. However, reverse causality is possible if swimmers in the last positions within swim groups only manage to catch up towards the end of the swim segment and are, in general, more skilled and/or performing athletes. Additionally, a strong correlation between passive drag and  $V' O_2$  max could also indicate that stronger athletes also experience greater passive drag Chatard et al. (1990), assuming this result applies also to real-world race settings.

#### *Unobservables and COVID-19 event regulations*

Single catching-up scenarios cannot be fully accounted for in the estimated models. The potential bias introduced by such instances is assumed to be uniformly distributed across all race observations. Special consideration is given to regulatory constraints, such as the COVID-19 rule prohibiting overtaking in specific course segments. These restrictions further influence race drafting opportunities throughout the swim segment, ultimately affecting overall mean race outcomes for drafters. Additionally, different observable course configurations, such as triangular and circular swim courses, shape drafting benefits and race dynamics. Furthermore, Buoy placements create tactical points that influence overtaking and positioning strategies, particularly in multi-lap races where swimmers navigate the same course multiple times before exiting the swim segment.

#### **Estimation framework**

To estimate the impact of swim drafting on Swim-Out performance, I employ a Two-Way Fixed Effects (TWFE) model, controlling for both athlete- and event-specific heterogeneity. The general estimation equation can be written in the form of:

$$ya_{ert} = \beta_0 + \beta_1 Leader_{aert} + \sum \beta_p Drafter(p) + \theta T X_{aert} + \eta_{et} + \eta_a + \varepsilon_{aert}$$

$p = 1$ .

where  $ya_{ert}$  represents the Swim-Out performance (e.g., swim time) of athlete  $a$  in event  $e$ , stored as race result  $r$ , at time  $t$ . The encoded binary dummy variables  $Leader_{aert}$  and  $Drafter(p)$  indicate drafting positions, while the vector  $X_{aert}$  contains relevant controls, including the overall race rank or constructed cluster rank (Swim Group) in the swim segment.

The fixed effects  $\eta_a$  account for athlete heterogeneity, while  $\eta_{et}$  captures event-time-specific shocks such as weather conditions, water temperature, or changes in race regulations. (e.g. wet suit allowance).

To explore period heterogeneity in drafting effects, I estimate a second specification with interaction terms:

$$ya_{ert} = \beta_0 + Drafter_{aert} \times (\beta_1 PrePeriod_t + \beta_2 COVIDYear_t) + \theta T X_{aert} + \eta_{et} + \eta_a + \varepsilon_{aert}$$

This model allows us to estimate whether the effect of drafting changed over time, particularly before, during, and after COVID-19, when race regulations varied significantly.

#### *Clustered, robust, and twfe standard errors*

To ensure reliable statistical inference, I employ various robust standard error estimators that account for heteroskedasticity and correlations within athletes across multiple events.

#### *Heteroskedasticity-Robust (HC1) standard errors*

To address potential heteroskedasticity—where the variability of errors differs across observations—I use a robust standard error estimator. This approach adjusts the standard errors to remain valid even when the underlying variance structure is inconsistent across data points.

#### *Clustered standard errors at the athlete level*

To account for the fact that individual athletes may participate in multiple events, I cluster standard errors at the athlete level. This method ensures that the estimated errors account for within-athlete correlations, leading to more accurate inference when analyzing repeated observations from the same athlete.

#### *Clustered standard errors at the athlete and event level*

Since dependencies may arise not only within athletes but also within events, I implement a multi-way clustering approach. This accounts for common influences affecting all participants in a specific event, such as environmental factors, drafting regulations, group dynamics, and other shared conditions. By doing so, the standard error estimates better reflect the true underlying variation present in the data.

#### *Two-Way Fixed Effects (TWFE) standard errors*

To further control for unobserved heterogeneity across both athlete and event dimensions, I employ the Two-Way Fixed Effects (TWFE) variance estimator. This approach removes systematic differences associated with individual athletes and specific events, ensuring that standard error estimates are robust to persistent unobserved factors. By eliminating these fixed effects, the estimator better isolates the true effect of interest while maintaining statistical validity.

## RESULTS

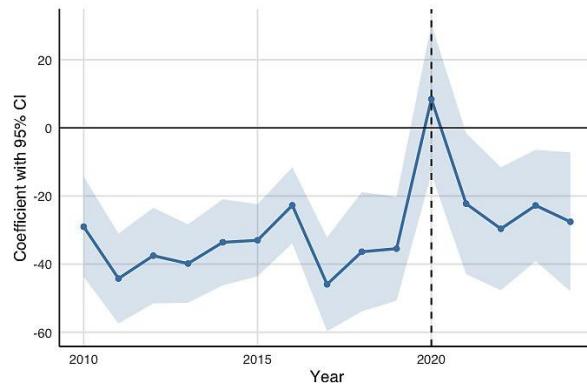
### ***The COVID-19 response policy induced event***

During the pandemic, individually staggered race starts and precautionary COVID-19 measures rendered the benefits of open-water swim drafting statistically insignificant in 2020. In the years following the pandemic, the estimated effects of drafting appear to be somewhat less pronounced. This trend is found to be particularly evident in a subsample of athletes who competed across all time periods, potentially due to COVID-19-related health shocks, changes in training behavior, or panel data limitations such as attrition.

### ***The effect of higher-order drafting positions***

Drafting is beneficial compared to the leader (based purely on swim-out segment performance time) only when an athlete is in at least the third drafting position within a swim group constructed based on clustered swim-out times. Drafting positions 1 and 2 are therefore strategic primarily as positions to minimize fatigue and strain before the subsequent bike leg in triathlon races. Delextrat et al. (2003) Since swim groups are constructed based on swim-out times, there may be some degree of endogeneity in the estimates. This could arise because athletes who manage to catch up to a swim group toward the end of the swim segment might influence their position within the swim group, potentially leading to biased results. To mitigate some of this

endogeneity, athlete and event fixed effects are employed. The inversely decaying nature of swim drafting benefits addresses at least some possible concerns of simultaneous reverse causality and partially also omitted variable bias.



Note. The solid thin line at 0 represents the baseline with no effect. The dashed vertical line at  $x = 2020$  marks the year when mass starts were disallowed at many events as a precautionary measure due to the COVID-19 pandemic. Furthermore, COVID-19 related race regulations were in place. In this year the coefficient of computed drafter is found to be insignificant.

Figure 1: Drafting benefits based on non-random yearly sub-samples: Coefficient plot.

Table 3. OLS estimation results - Dependent variable: swim out times.

	Estimate	Std. Error	t-value	Pr(> t )
Drafter	-23.8886	4.1184	-5.8004	$6.63 \times 10^{-9}$ ***
Pre-period $\times$ Drafter	-8.5779	4.6013	-1.8642	0.0623
COVID-year $\times$ Drafter	19.4150	8.1469	2.3831	0.0172 *
Observations	168,391			
Fixed-effects	Athlete ID: 29,194, Event ID: 1,339, Cluster (Swim Group): 224			
Standard-errors	Heteroskedasticity-robust			
RMSE	175.1			
Adj. R <sup>2</sup>	0.9683			
Within R <sup>2</sup>	0.0035			

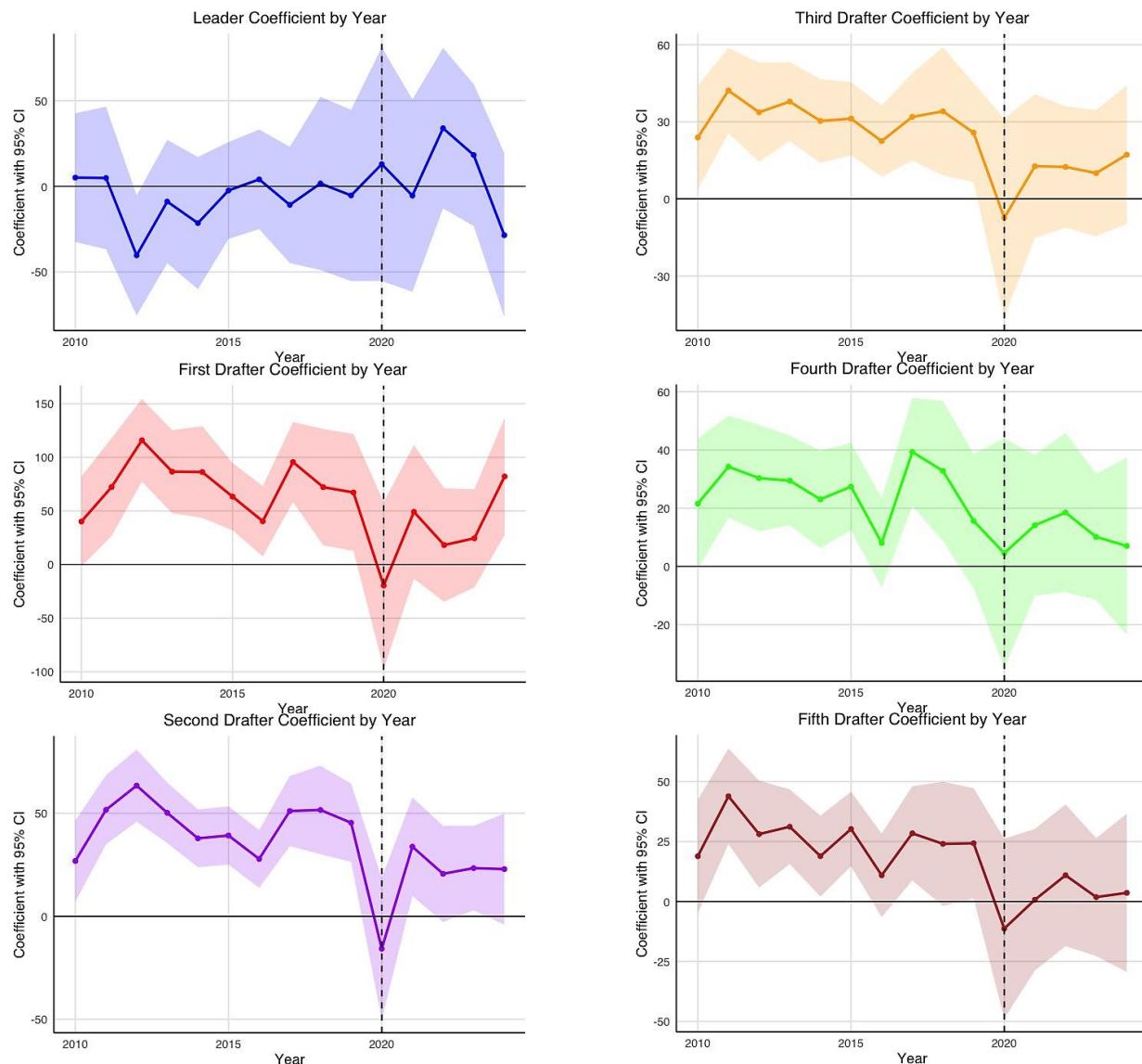
Notes. The dependent variable is *Swim-Out Times* performance (time in seconds). Fixed-effects regression includes athlete ID, event ID, and computed swim group cluster in event. Periods: The variable pre-period is a dummy indicating events before 2020. The variable COVID-year is a dummy indicating events in 2020. Swim groups: Clusters are determined by hierarchical clustering with a threshold of 5 seconds. Dummies: The drafter dummy is 1 for non-leaders of swim groups. The pre-period \* drafter interaction tests the effect of drafting before 2020. The COVID-year \* drafter interaction examines the drafting effect in 2020. Significance codes: \*\*\*  $p < .001$ , \*\*  $p < .01$ , \*  $p < .05$ , .  $p < .1$ .

Table 4. Combined drafting position dummies fe model estimation results.

	Model 1	Model 2	Model 5	Model 6
Leader	0.8688 (3.9616)	13.7712*** (3.7570)	30.8295*** (1.4979)	30.4761*** (1.4965)
Leader x Cluster (SG)	-	-	-	1.2926*** (0.1264)
Cluster (SG)	-	-	-	0.6579*** (0.0862)
Race Rank	-	-	-	0.3967*** (0.0072)
First Drafter	46.8571*** (4.3806)	17.8360*** (3.9534)	-	48.5491*** (4.2379)
Second Drafter	26.0330*** (1.8769)	-	-	31.2118*** (1.7903)
Third Drafter	19.4259*** (1.8238)	-	-	23.5610*** (1.7470)

Fourth Drafter	17.4769*** (1.9906)	-	6.0963** (1.8925)	19.6363*** (1.8914)
Fifth Drafter	15.3214*** (2.0454)	-	-	15.4568*** (1.9386)
Observations	168,391	168,391	168,391	168,391
RMSE	175.0	175.1	175.1	169.2
Adj. R <sup>2</sup>	0.9684	0.9683	0.9683	0.9705
Within R <sup>2</sup>	0.0050	0.0035	0.0034	0.1131

Notes. This table presents the results of six fixed-effects OLS estimations. OLS Estimation of FE Models (Dependent Variable: Swim-Out Time, Swim Group Def.: Max 5 sec. apart, Cluster (Swim Group) Single Linkage). The dependent variable is Swim- Out Times. Models include fixed effects for athlete\_id (29,194 levels) and event\_id (1,339 levels). Standard errors are robust to heteroskedasticity. Statistical significance: \*\*\*  $p < .001$ , \*\*  $p < .01$ , \*  $p < .05$ .



Note. Each model is estimated separately for every year from 2010 to 2024, controlling for individual athlete and event fixed effects. Notable drafting position dummies are found to have no significant penalty effect in 2020, when mass starts were disallowed as a precautionary measure at many events due to the COVID-19 pandemic. Higher-order drafting positions are found to have less pronounced penalties in any given year, making them more favorable.

Figure 2. Yearly coefficient plots from fixed-effects regressions estimating the impact of drafting positions and leadership on swim-out time performance.

## DISCUSSION

While I provide the first causal estimates of open-water swim drafting effects, several limitations should be acknowledged.

First, the estimation approach relies on inferred swim group structures based on clustered Swim-Out times, which may introduce measurement error. The classification of drafters and leaders remains an approximation rather than a direct observation.

Second, the staggered race starts during the COVID-19 pandemic serve as a natural experiment. However, unobserved factors, such as changes in athlete fitness levels, race-day conditions, or competition field strength, may have influenced drafting benefits across different periods, potentially confounding causal interpretations. This might have led to the only weak significance (at the 10% level) of the interaction term *Pre-period × Drafter* in Table 3.

Third, reverse causality remains a concern despite the inclusion of athlete- and event-fixed effects. More capable athletes may self-select into different drafting positions, catch up to swim groups over the course of a race, or utilize higher passive drag depending on their fitness level on race day. These dynamics could result in endogenous group formations, potentially biasing the estimated effects.

Finally, course-specific factors such as buoy placements, water currents, and water temperature—which influence wetsuit usage regulations—are not explicitly controlled for in the models. These factors may affect drafting effectiveness but are difficult to quantify systematically across different race events.

## CONCLUSION

This study provides the first large-scale causal estimate of open-water swim drafting effects in real-world triathlon race settings. Leveraging a natural experiment induced by staggered race starts during the COVID-19 pandemic, I find that drafting benefits were statistically insignificant in 2020 but re-emerged post-pandemic, albeit at slightly reduced levels. Our results indicate that drafting only becomes beneficial from the third trailing position onward, while earlier positions primarily serve to minimize fatigue or strategic purposes. By employing athlete and event fixed effects, I address potential heterogeneity concerns, and the observed inverse decay of drafting benefits helps to partially mitigate concerns related to endogeneity, reverse causality, and omitted variable bias. These findings offer valuable insights into optimal swim strategies for endurance athletes and race organizers.

## SUPPORTING AGENCIES

No funding agencies were reported by the author.

## DISCLOSURE STATEMENT

No potential conflict of interest was reported by the author.

## CONFIRMATION OF ETHICAL COMPLIANCE

The study adheres to ethical guidelines, and no human subjects were directly involved in the research.

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