Senior Swim Competition Times

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Abstract
We present a multivariate data set of 878 observations (395 men, 483 women) on 500-yard freestyle swim times in the biennial U.S. National Senior Games (ages 50 and up) in five successive NSGA competitions (2009, 2011, 2013, 2015, 2017). We ask: (1) What is the relationship between age and swim time, and how should it be modeled? (2) Do men and women exhibit the same patterns of change by age? (3) How well do seed times predict actual times? (4) Do competition years differ? (5) What is the pattern of split times (i.e., in each of the 10 laps)? We examine the time-age relationship using regression (OLS, quantile, bootstrap standard errors) with age category binaries as well as with quadratic and semi-log models of age. To predict time for a "typical" swimmer, we favor quantile regression (25%, 50%, 75%). Swim time increase is nonlinear after age 50, and women's average times increase more rapidly than men's. Competition year plays no consistent role. Seed times slightly overestimate actual time. Split times are faster in the first and last laps of the race and fairly level in between.

Key Words: Senior Athletes, Women in Sports, Quadratic Model, Semi-Log Model, Quantile Regression, Bootstrap

1. Background

The National Senior Games Association (NSGA) sponsors nationwide competitions during odd years. To participate in the NSGA Nationals, one must first qualify in a NSGA State Game during the preceding even year (e.g., 2016). Participants must be at least 50 years old during the qualifying year in the state where they live, or any state that allows out-of-state competitors. Summer Games medal sports include archery, badminton, basketball, bowling, cycling, golf, horseshoes, pickleball, race walk, racquetball, road race, shuffleboard, softball, swimming, table tennis, tennis, track and field, triathlon, and volleyball. In most sports (including swimming) the top 4 finishers in each age group qualify for Nationals. Competition is by age bracket in 5-year intervals (50-54, 55-59, … , 95-99). Our study examines swim times in the 500-yard freestyle (25-yard, short course) event in the Summer National Senior Games (ages 50 and up) in five successive biennial competitions (2009, 2011, 2013, 2015, 2017).

Because this is more of an endurance event, rather than a sprint, individual performance is less affected by random variation and is more reflective of stamina and training. On average, performance is expected to decline with age, but how should this be modeled and estimated? Do men and women show the same patterns of decline? We explore alternative model specifications, estimation techniques, and benchmarks so swimmers can compare their times against recent NSGA competitors. Our findings on the roles of age and gender are broadly consistent with other studies of elite competitors in the Olympics and U.S. Master's Swimming competitors. However, because our goals, methods, and database are different, our results should not be generalized beyond the biennial NSGA competitions.

Although the role of gender may be studied in regression using a gender binary and interaction terms, students will find it more natural to estimate each gender separately. We report parameter estimates for each gender using both OLS and quantile regression (25%, 50%, 75%). Aside from the effects of age and gender, our rich data set permits us to study additional questions. Do times differ by year? What is the pattern of split times (i.e., in each of the 10 laps)? Do age and gender affect starting platform reaction times (time from the starting buzzer to when the swimmer's weight actually leaves the platform)? How well do qualifying seed times predict actual meet times?

2. Data

Our data set has 878 observations (395 men, 483 women) and 40 variables. Contact doane@oakland.edu to obtain the data (Excel format).

Obs	observation in sorted list (year, gender, age group, place)
Place	finish order in age group for that year
Name	name of each participant (omitted in shared data set)
State	participant's qualifying state
Gender	0 = male, 1 = female
Age	age in years
Age2	age squared (for non-linearity tests)
AgeGrp	age group in 5-year bins: 1=50-54, 2=55-59, … , etc.)
A1…A10	age group binaries (e.g., A1=1 if 50-54, 0 otherwise, etc.)
Year	competition year (2009, 2011, 2013, 2015, 2017)
Y9…Y17	0-1 binaries for year (e.g., Y9=1 if 2009, 0 otherwise, etc.)
Seed	qualifying time prior to national competition
Time	swim time in race (seconds)
Time-Seed	difference between actual time and seed time
lnTime	natural logarithm of Time
S1…S10	time (seconds) in each 50-yard split (ten data columns)
NumEst	number of lap times that were estimated
*Num**	number of missing lap times

We have deliberately created variables (e.g., *lnTime* and *Age2*) that are intended to lead students to examine specific questions, such as whether the relationship between *Time* and *Age* should be modeled as non-linear. We have created categorical variables to encourage students to look at specific *Time* patterns (e.g., by year and by split). We also included age categories to permit model-free investigation of the relationship between *Time* and *Age*. This is a rich data set whose characteristics cannot be inferred without data analysis, hence being useful for class demonstrations or student team projects.

While data accuracy is generally high, a few issues exist. For example, some split times were missing. The 500-yard race consists of ten 50-yard laps (20 lengths of 25 yards). Each 50-yard lap is a *split*. The swimmer touches an electronic pad at the end of each lap. Occasionally, a swimmer touches with hands above the pad or pushes off so lightly that the touch is not recorded. This is more common with older swimmers, who also may avoid flip turns. In addition, electronic touchpads may vary in their sensitivity, may be imperfectly calibrated, or may have "dead spots." Human spotters will report if the swimmer actually fails to touch, which would disqualify the time and would not be part of our data. If only one touch was unrecorded, we estimated the missing split time as half the time between the adjacent touches. Otherwise, a split time was recorded as missing.

As a further accuracy check, the ten split times should sum to the total time. If not, it was sometimes possible to reconcile the difference by examining raw timer data. We had access to some detailed data for individual participants, which allowed us to retain many of the discrepant observations.

Another problem was high extremes. While there is a physiological lower limit on swim times, there is no upper limit. For example, a swimmer may suffer cramps or may simply need to slow down. Senior swimmers are philosophical about their limitations and are more willing to "back off" than a younger athlete might be. Residuals, therefore, will be positively skewed and may contain extremes.

Selection bias is also a concern. Many eligible swimmers (the top four per state) decline to participate in the nationals. This is partly a financial matter. The cost of hotel, meals, and travel to the host city (2009 San Francisco, 2011 Houston, 2013 Cleveland, 2015 Minneapolis, 2017 Birmingham) can be daunting. The summer games last for two weeks, and many athletes compete in multiple events (up to six) so hotel and meal costs add up. Health problems force some athlete to drop out after qualifying, or to enter only the events in which they have the best chance. A few may judge that their medal chances are too low to justify the trip. Some states have well-organized senior swim teams that encourage and support participation, while others have none. The effect is to reduce the potential sample size substantially.

3. Initial Data Exploration

The age distribution of participants in our database is shown in Figure 1. Male and female swimmers have similar patterns, with two modes (ages 60-64 and 70-74). As would be expected, there are fewer participants in higher age categories.

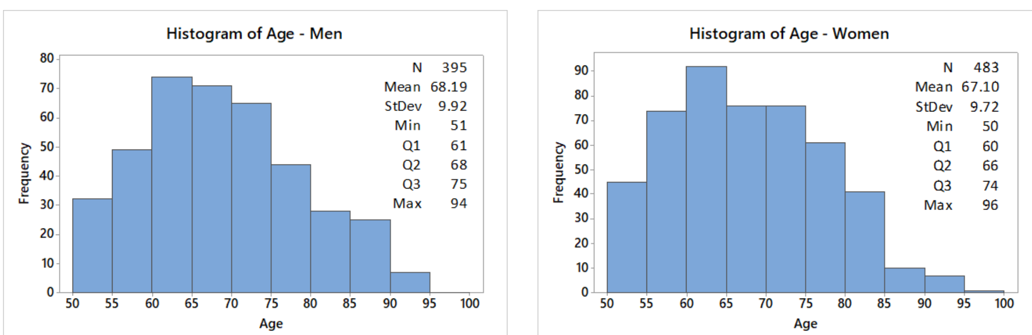

Figure 1: Distribution of swimmers by age group

Our first regression employs 5-year age group dummy (0-1) variables: A1 (50-54), A2 (55-59), A3 (60-64), A4 (65-69), A5 (70-74), A6 (75-79), A7 (80-84), A8 (85-89), A9 (90-94), A10 (95-99). This has the advantage of avoiding a specific model form. We omit A1 so that age group 50-54 becomes the base. We estimate OLS regressions separately for each gender as shown in Tables 1 and 2.

Table 1: Age Binary Regression Coefficients: Men

	All Men (n = 395)		*Omit Two (n = 395)*	
Predictor	*Coef*	*t*	*Coef*	*t*
Intercept	396.6	19.43	396.6	22.69
A2	4.5	0.17	4.5	0.20
A3	44.3	1.82	33.5	1.60
A4	85.9	3.50	85.9	4.08
A5	147.1	5.90	133.6	6.24
A6	170.6	6.36	170.6	7.43
A7	204.6	6.85	204.6	8.00
A8	409.0	13.27	409.0	15.50
A9	518.8	10.77	518.8	12.57
n	395		393	
s	115.445		98.874	
R^2	50.17%		58.31%	

The estimated age group coefficients for men increase with age as would be expected (Table 1). However, the A2 coefficient is effectively zero, suggesting that average times for ages 55-59 (A2) are about the same as for ages 50-54 (A1). Two unusually slow swim times (standardized residuals 6.89 and 7.54 respectively) pose a problem. These two individuals had swim times that were almost three times their predicted times. Omitting these two atypical observations greatly improves the fit (last two columns). The estimated coefficients are the same except for A3 and A5 (highlighted). In subsequent regressions, we choose to omit these two observations (n = 393 instead of n = 395) to obtain more realistic performance benchmarks for typical contestants.

Table 2: Age Binary Regression Coefficients: Women

	All Women (n = 483)		*Omit One (n = 482)*	
Term	*Coef*	*t*	*Coef*	*t*
Constant	456.2	25.33	456.2	26.16
A2	16.9	0.74	16.9	0.77
A3	82.2	3.74	82.2	3.86
A4	150.8	6.64	150.8	6.86
A5	192.1	8.45	192.1	8.73
A6	273.4	11.51	262.3	11.37
A7	332.2	12.74	332.2	13.15
A8	533.5	12.63	533.5	13.05
A9	603.1	12.29	603.1	12.69
A10	887.0	7.26	887.0	7.50
n	483		482	
s	120.813		116.974	
R^2	55.47%		56.64%	

For women, as with men, the age binary coefficients for women increase with age as would be expected (Table 2). However, as with the men, the A2 coefficient is effectively zero, suggesting that average times for age 55-59 (A2) are almost the same as for age 50-54 (A1). One slow swimmer (standardized residual 5.52) has a noticeable effect on the standard error (and on the coefficient for age category A6, highlighted). Her time was twice its fitted value. In subsequent regressions, we will omit this observation (n = 482 instead of n = 483) to obtain more realistic performance benchmarks for typical swimmers. Figure 2 shows predicted times by age category. Expected swim times deteriorate more than linearly, suggesting that we should examine non-linear models of the age-time relationship.

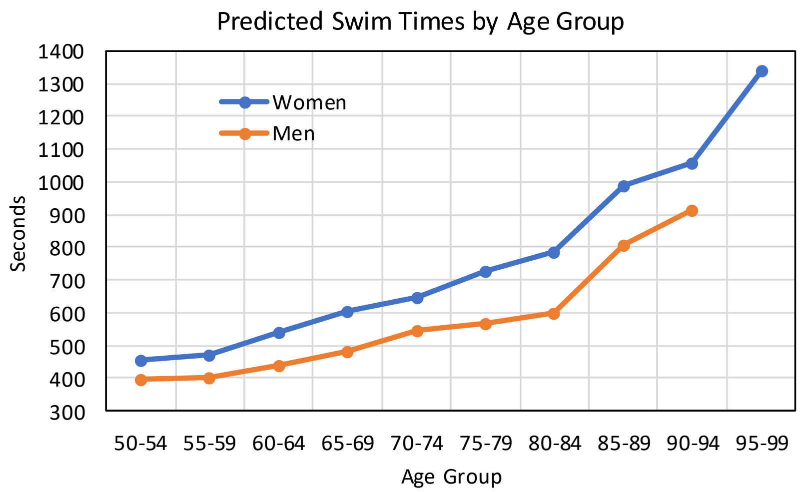

Figure 2: Predictions Using Age Binaries

4. Quadratic Model

One way to capture nonlinearity is the quadratic model $Time = \beta_0 + \beta_1 \text{ Age} + \beta_2 Age^2$. We wanted to see whether there was any difference in swim times by competition year, so we coded 0-1 dummy variables (Y9, Y11, Y13, Y15, Y17) for the years (2009, 2011, 2013, 2015, 2017). The OLS estimates (Table 3) suggest that, for men, there is no difference in years (Y9 was omitted so 2009 is the base year). Women's times seem to have been consistently faster since 2009. Perhaps recent biennial competitions became stiffer? Aside from noting this interesting phenomenon, it seems best to ignore competition year as a predictor on grounds that there is no logical way to incorporate it into a predictive model.

Table 3: Quadratic Regression Coefficients with Year Binaries

	Men (n = 393)		*Women (n = 482)*	
Term	*Coef*	*t*	*Coef*	*t*
Constant	1240	5.72	842	3.69
Age	-32.32	-5.17	-19.51	-2.90
Age2	0.3101	6.96	0.2400	4.93
Y11	13.8	0.89	-31.1	-2.00
Y13	-9.2	-0.61	-36.2	-2.22
Y15	2.2	0.14	-32.6	-1.91
Y17	1.7	0.11	-27.0	-1.60
s	98.783		115.797	
R^2	58.17%		57.25%	

We estimated the quadratic model without year binaries for each gender separately, using OLS (Minitab 18) and quantile regression (Stata *bsqreg* with bootstrapped standard errors). We fitted 25%, 50%, 75% quantiles. To facilitate comparison with OLS, Table 4 shows only the median (50%) quantile results
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Table 4: Estimated Quadratic Regression Coefficients

	OLS Regression Coefficients				*Median Coefficients*			
Predictor	*Men*	*t*	*Women*	*t*	*Men*	*t*	*Women*	*t*
Constant	1244	5.80	843	3.68	1066	3.87	1036	4.53
Age	-32.42	-5.23	-20.14	-2.99	-27.77	-3.17	-26.67	-3.97
Age2	0.3109	7.04	0.2437	4.99	0.2781	4.03	0.2934	6.07
s	98.551		116.104		----		----	
R^2	57.93%		56.65%		----		----	

Because quantile regression minimizes the sum of the absolute residuals rather than the sum of the squared residuals, we do not get a comparable standard error or R^2. While the OLS and median (50%) coefficients differ, the implied function shape and predictions are similar, as shown in Figure 3. For either gender, the OLS prediction (conditional mean) is usually a bit higher than the 50% quantile prediction (conditional median) because median coefficient estimates are less affected by high extremes (i.e., the unusually slow swimmers). While the differences for between OLS and 50% quantile may appear small on this scale, they can represent a pool length for some age groups.

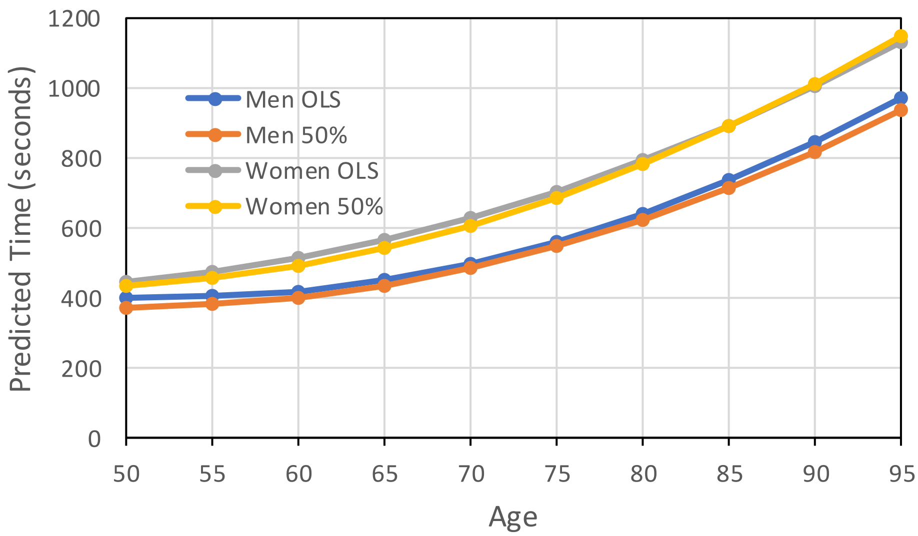

Figure 3: Predictions Using Quadratic Model

Teaching Idea #1
An interesting class demonstration (or student exercise) would be to solve for the implied minimum on the quadratic function. We equate *d*(*Time*)/*d*(*Age*) to zero and solve for the "best" age (denoted *Age**). Using the OLS estimated coefficients:

For men:
$Time = 1244 - 32.42\ Age + 0.3109\ Age^2$
$d(Time)/d(Age) = -32.42 + 2(0.3109)\ Age$
$Age^* = (32.42)/(0.6218) = 52.1$ years

For women:
$Time = 843 - 20.14\ Age + 0.2437\ Age^2$
$d(Time)/d(Age) = -20.14 + 2(0.2437)\ Age$
$Age^* = (20.14)/(0.4874) = 41.3$ years

For men, the "best" age is 52 while for women it is 41 (or 50 and 45 respectively if we solve using the median coefficients). Women appear to reach their best times at an earlier age than men. But if our sample had included swimmers of all ages, we would expect the "best" age to be earlier, so this should not be interpreted as the "best" age for all swimmers. Worthy of discussion with students.

Teaching Idea #2

Is the quadratic function form too restrictive? Is the main question how swim time deteriorates after age 50? We used Excel's Solver to fit the model $Time = b_0 + (Age-50)^{b1}$ with an objective of minimizing of $\sum e_i^2$ The results were:

Men: $Time = 368.9612 + (Age\text{-}50)^{1.653486}$
Fem: $Time = 458.6627 + (Age\text{-}50)^{1.708483}$

These results suggest that, after age 50, women slow down faster than men. This exercise is within reach of students who have learned to use Excel's Solver. The only tricky part is that Solver requires reasonable seeds for parameter estimation. An instructor can suggest choosing the intercept seed as any 50-year old swimmer's time and exponent seed 1 or 2.

Teaching Idea #3

Quantile regression offers another teaching opportunity. Although students may lack access to quantile regression software, it is useful to discuss alternatives to ordinary least squares, e.g., minimizing $\sum|e_i|$ instead of minimizing $\sum e_i^2$. There is no calculus-based solution to the former problem, so quantile estimation requires linear programming. While the computations are not simple, students can grasp that a median estimate is likely to be more robust to violations of the OLS assumptions (e.g., nonnormality). Many universities do have licenses for statistical packages such as Stata to handled quantile computations, and the R proc *quantreg* in the CRAN repository is well documented. One or two students could be asked to research quantile regression on the web and give a short presentation to the class what they have learned.

Residual Tests

We expected the distribution of OLS residuals to be positively skewed, as there is no limit on how slow a swimmer can be while even the best swimmers face an asymptotic limit on ability. The residual plots for the OLS regressions (Figure 4) suggest that OLS might also benefit from using bootstrap standard error for our *t*-tests. These plots also suggest the futility of trying to trim unusual observations.

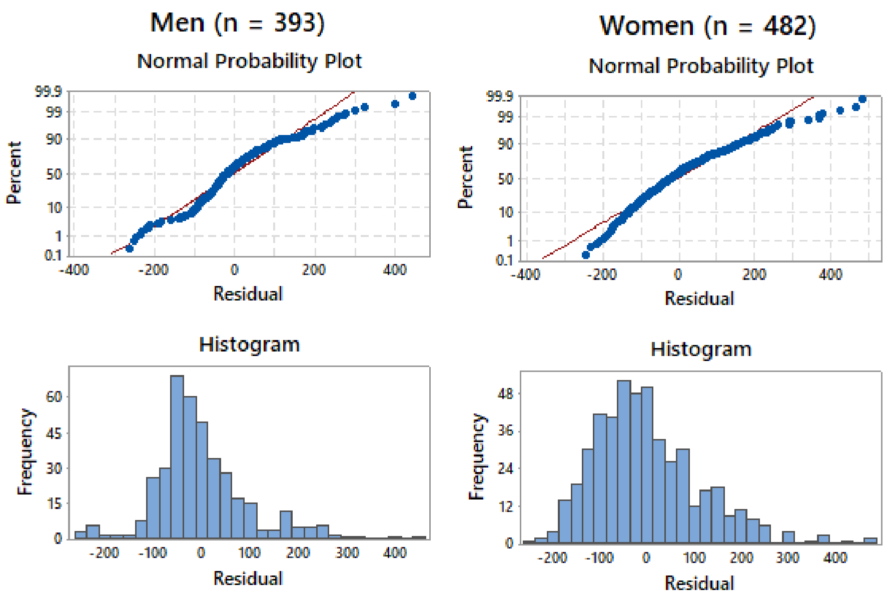

Figure 4: Predictions Using Age Binaries

5. Semilog Model

We specify the semilog model as ln(*Time*) = $\beta_0 + \beta_1$ *Age*. We estimate each gender separately using OLS and quantile (median) regression, as summarized in Table 3.

Table 3: Estimated Semi-Log Regression Coefficients – Separate Genders

	OLS Regression Coefficients				*Median Regression Coefficients*			
Term	*Men*	*t*	*Women*	*t*	*Men*	*t*	*Women*	*t*
Constant	4.8496	79.77	4.9821	87.77	4.850799	74.04	4.88394	65.05
age	0.019757	22.39	0.020809	24.85	0.0193568	20.08	0.0220744	19.91
s	0.173562		0.178432		----		----	
R^2	56.18%		56.26%		----		----	

The semilog predictions (Figure 5) also show that swim times deteriorate non-linearly with age, although not as steeply as the quadratic model. A "typical" swimmer would probably find the median (50%) predictions from the semilog model to be a realistic guide to the competition. An attraction of the semi-log model is its conformance to what one might expect based on human physiology (i.e., steady deterioration past age 50). However, unlike the quadratic model, the log model allows no point of inflection.

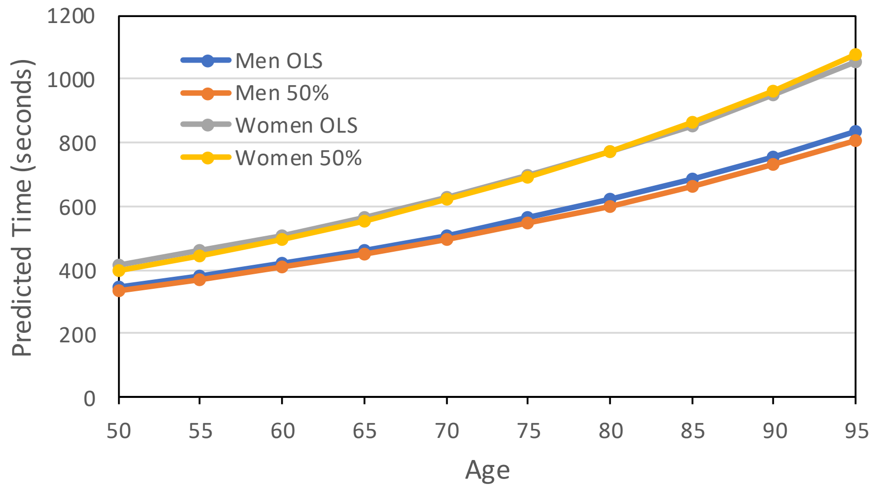

Figure 5: Semilog Model Predictions

While these predictions appear similar on this scale, a closer look (Figure 6) at the differences between OLS and median (50%) predictions) reveals a systematic difference that could be important, particularly to swimmers older than 80.

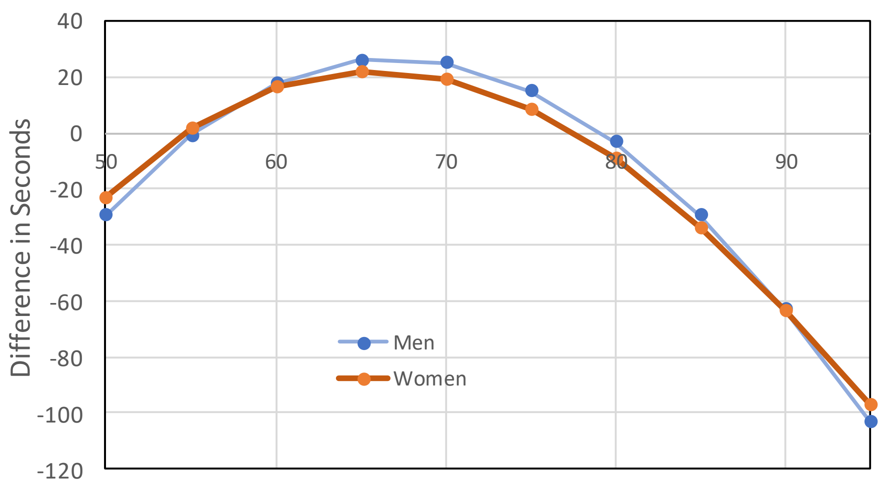

Figure 6: Difference Between OLS and Median Predictions for Semilog Model

Teaching Idea #4

Have students estimate a regression combining both genders using a gender binary (*Gender* = 0, 1) and an interaction term. For example, the semilog model would be ln(*Time*) = β_0 + β_1 *Age* + β_2 *Gender* + β_3 *Age*Gender*. Do the results support the conclusions from estimating each gender separately? What are the advantages and disadvantages of each approach? Is separating the genders easier to interpret and explain? These questions can be discussed in class, or students can explore them on their own.

Other Quantiles

Figure 7 shows the estimated 25%, 50%, and 75% quantiles plotted on the entire 2009-2017 data set for each gender. Scales do not start at zero to show more detail. Given the recent number of competitors in each age group, a swimmer in the fastest 25 percent would have a reasonable chance of placing in the top 8, thereby qualifying for recognition on the winner's dais (but only the top 3 receive medals).

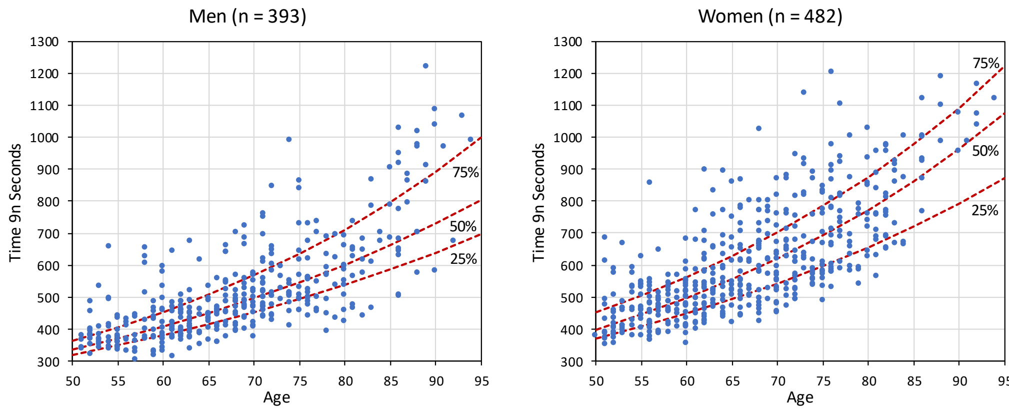

Figure 7: Quantile Regression Predictions

A swimmer who plans to compete in NSGA Summer Games can assess his/her relative standing against competitors in recent biennial NSGA competitions using the estimated semilog models shown below. The 2019 NSGA competition could be used as a test.

Men:

25% quantile:	$Time = \exp(4.898135{+}0.0173513\, Age)$
50% quantile:	$Time = \exp(4.850799{+}0.0193568\, Age)$
75% quantile:	$Time = \exp(4.769993{+}0.0224767\, Age)$

Women:

25% quantile:	$Time = \exp(4.972687{+}0.0189086\, Age)$
50% quantile:	$Time = \exp(4.883940{+}0.0220744\, Age)$
75% quantile*:	$Time = \exp(5.004823{+}0.0221311\, Age)$

6. Comparison with Existing Research

The effects of age and gender on athletic performance have been analyzed extensively, including swim times, both in cross-sectional and longitudinal studies. In these studies, data become sparse toward the highest ages. Swimming research has utilized results from U.S. Master's Swimming competitions (Rubin and Rahe 2010, 2013) and has focused on best times by elite swimmers in a variety of events (e.g., Fairbrother 2007; Donato *et al* 2003; Konig *et al* 2014; Rust *et al* 2014). Despite a focus on sex differences (e.g., Wild *et al*, 2014) the "peak" age is addressed (e.g., Rust *et al* 2014). Yet research on elite swimmers (including younger ones) has a different application than our research on swimmers of varied ability aged 50 and over. Studies of the 800 m or 1500 m endurance events (e.g., Tanaka and Seals, 1997; Fairbrother, 2007) are somewhat comparable to ours. Researchers have used the quadratic model or hierarchical regression (e.g., Rust *et al*, 2014) to capture nonlinearity, although we also see linear regression (e.g., Rahe and Arthur, 1975), the semi-log model (e.g., Rubin *et al* 2013), and correlation analysis (e.g., Konig *et al* 2014). An interesting recent study compares 5-year age groups like ours, but it starts at age 25-29 (whereas we start at 50-54). Studies generally support our conclusion that swim times deteriorate non-linearly with age, especially after age 70.

While our results cannot easily be compared with other studies, given differences in ages covered, race length, and data sources, our fitted models and gender conclusions resemble those in other research. Our use of quantile regression adds a useful new perspective, and our 50-and-over NSGA data provide realistic benchmarks for "typical" senior swimmers of various abilities.

7. Split Times

Figure 8 shows standardized split times for 100 randomly-chosen swimmers (both genders). For each swimmer, we divided each split time (*Split*) by the swimmer's average split time (*Time*/10) in the 500-yard race. Thus, the reference point 1.00 would be an "average" split time for that swimmer. The first 50-yard split (denoted S1 in Figure 8) is faster because of the dive from the starting platform. An exception would be swimmers who choose (because of age or health issues) to start in the water rather than risk a dive, or who have trouble getting up onto the platform (a problem especially for swimmers age 75 and over). The second split (S2) usually is also faster because of the "adrenalin" factor at the race's start (crowd noise, etc). The middle laps (S3-S9) tend to be "just swimming." The final 50-yard split (denoted S10) typically is faster as the swimmer makes a strong finishing effort.

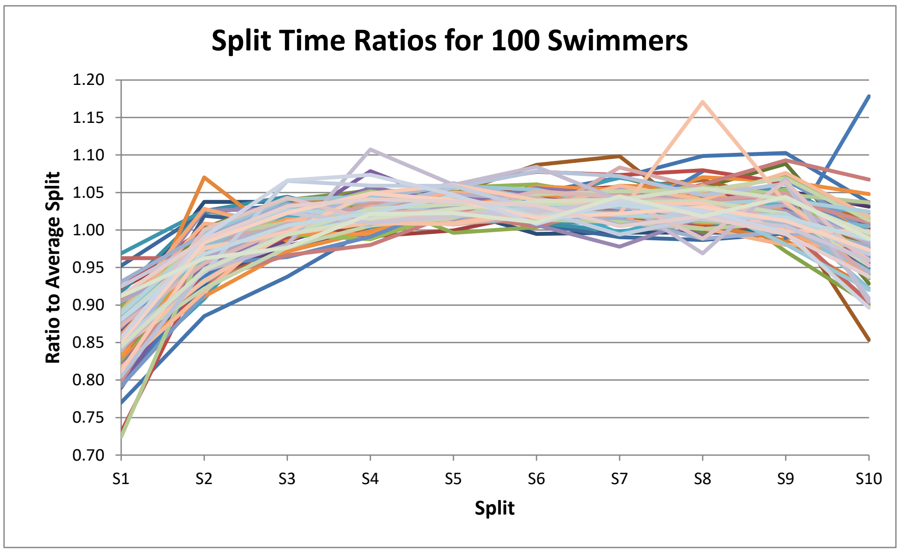

Figure 8: Split Time Ratios for 100 Swimmers

There is obviously a great deal of variation, but a pattern also exists. To see the pattern more clearly, we took averages over all swimmers (by gender) as displayed in Figure 9 (omitting any missing or estimated split times). Women's and men's patterns are essentially the same. Good strategy requires a swimmer to know her/his capabilities and to regulate the pace. Swimmers must balance "type I error" (over-doing it in early laps, then fading) against "type II error" (conserving too much, then unable to catch up). Experienced swimmers swim against themselves as much as against others, who may be hard to see clearly.

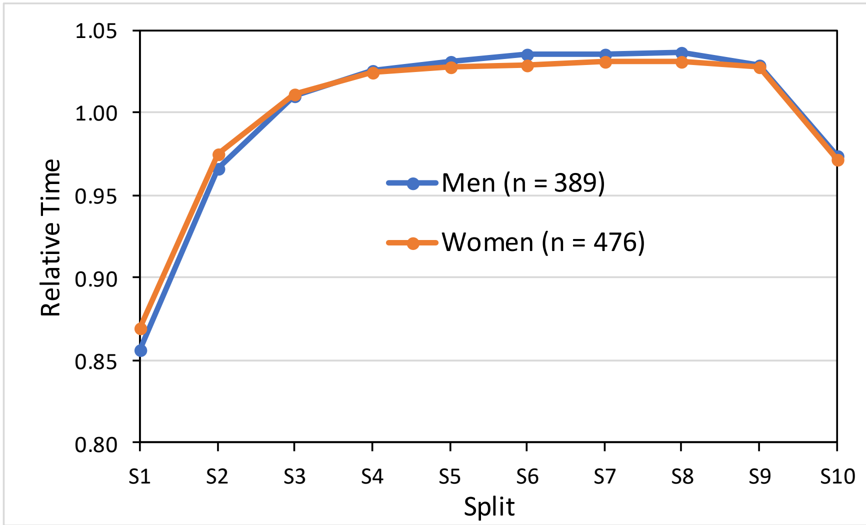

Figure 9: Relative Split Time Averaged Over All Swimmers

8. Reaction Times

For one year (2011) we data on the time (seconds) from the sound of the starting buzzer until the time the swimmer's weight left the starting platform. Figure 10 shows the distributions of these reaction times. The statistics for women and men are almost identical. For men, the Anderson-Darling test suggests a normal distribution (p = .67) but not for women (p = .049).

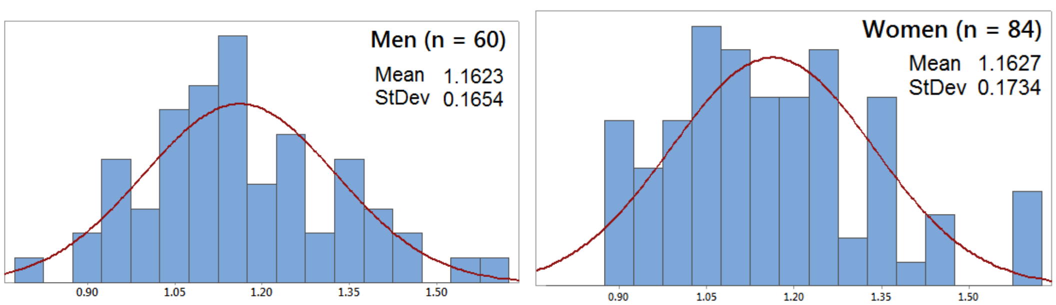

Figure 10: Reaction Times for Starting Platform

Does reaction time deteriorate with age? Not to a noticeable degree, as shown in Figure 11. While the regression has a positive slope, the scatter plot says that the effect is of no practical importance. It is interesting that the oldest competitor (a 94-year old woman) got off the platform quicker than some younger swimmers. In this illustration, both genders are combined because tests showed no significant differences by gender (t-tests of means were insignificant and fitted regressions were almost identical).

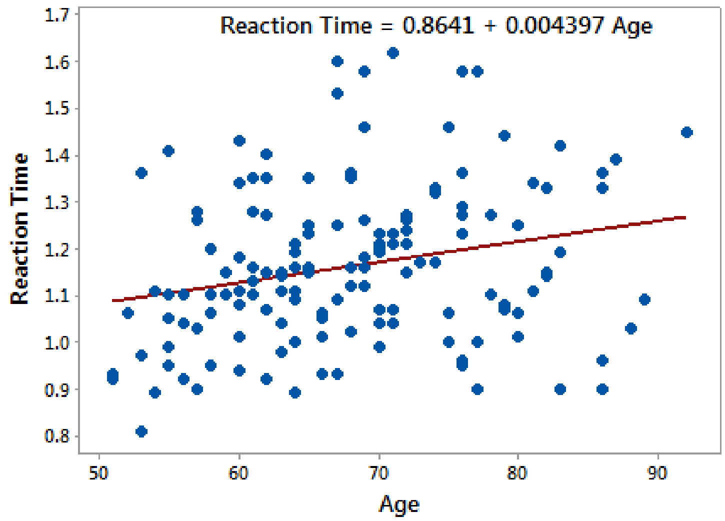

Figure 11: Reaction Times versus Age (both genders combined)

9. Seed Times

One more question that we studied was how well a swimmer's qualifying time ("seed") predicts the actual time. The seed time is usually the best time in state competitions prior to the nationals. Seed times are provided to NSGA competitors prior to the finals in "psych sheets" (this title emphasizes the psychological aspect of competitive swimming). Figure 12 shows that seed time predicts national time very well. However, for both genders, the national competition time is better, on average, than seed time (slope less than 1). Presumably, the national competition brings forth extra effort in most swimmers.

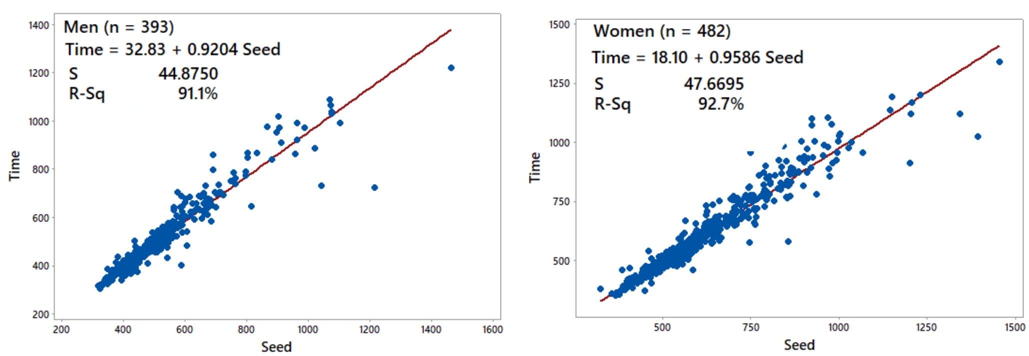

Figure 12: Seed Time as Predictor of Actual Time

10. Conclusions

While we cannot generalize beyond NSGA competitions, our empirical observations about age, gender, split times, reaction times, and seed times are reasonable *a priori*. At a minimum, our analysis provides a reference point for future empirical research. We speculate that Title IX may reduce the male-female gap as more women participate in competitive swimming. although swimming is a sport where equality of opportunity already has a fairly long history. Over time, we predict tougher competition in *senior* swim meets because many senior swimmers today are self-taught. Competitive swim training nowadays starts as early as young as age 6 (e.g., USA Swimming, YMCA Live Y'ers). As these youths age, they are likely to be formidable senior competitors.

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