

A ZERO-INFLATED ANALYSIS OF THE 2020 TOUR DE FRANCE

BY GIAN CARLO DI-LUVI*,

*University of British Columbia**

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

1. Introduction.

2. Data description. The data contain information of each cyclist and stage of the 2020 Tour de France. A summary of all the variables included in the data set can be found in Table 1. The data are public and was scraped from the [Tour's official website](#) using `Python` and the [2020 Tour de France Wikipedia](#) page by hand. It was then combined into a single data set containing 3,390 observations and 23 variables.

Each row corresponds to an observation and each column to a variable. The observations are at the “rider by stage” level, i.e., each observation corresponds to a rider at a given stage. Some variables, such as the winner country, are constant across stages. The number of riders is not the same at each stage because some riders leave the race due to injuries. Specifically, 175 riders started the tour but only 146 finished it.¹ There are five different stage types in this data set: flat, medium mountain, hilly, mountain, and mountain time trial. Other stage types exist in the sport but were not included in this year's Tour de France (e.g. team time trial). The cumulative time is determined as the sum of the times at each stage, minus the total bonus seconds, plus the total penalty seconds. Bonus points are awarded to the first three riders to finish each stage; penalties are imposed when cyclists break rules, such as receiving food close to the finish line. Finally, race leader is used interchangeably with general classification leader because that is the most important event of the Tour, even though there are many races going on at the same time.

¹Notably, Egan Bernal, last year's winner, left the Tour after stage 16 due to back pain.

Variable	Description	Type of variable
rank	rider's rank at that stage	float
rider	rider's name	string
rider_number	rider's bib number	integer
team	rider's team	string
time	rider's time in that stage	string
bonus	rider's bonus seconds in that stage	float
penalty	rider's penalty seconds in that stage	float
stage	stage number	integer
date	date of stage	date
distance	distance of stage	float
origin	origin of stage	string
destination	destination of stage	string
stage_type	type of stage (mountain, flat, etc.)	string
winner_country	country of rider who won stage	string
general	bib number of rider leading the race	integer
points	bib number of rider leading the points race	integer
mountains	bib number of rider leading the mountains race	integer
young	bib number of rider leading the young race	integer
stage_winner	bib number of rider that won the stage	integer
time_seconds	rider's time in seconds in that stage	float
cum_time	rider's cumulative time at that stage (including bonus and penalty seconds)	float
gc_rank	rider's rank in the general classification	integer
timediff	rider's time difference in seconds to race leader	float

TABLE 1
Variables included in the data set.

3. Exploratory data analysis. Stage number plays an important role because, as the race progresses, the riders become more tired. There were two rest days between stages 9 and 10 and 15 and 16. Tour de France riders can recover at faster rates than average people, so that their performance after a rest day could be similar to their performance during the Tour's first stage. In any case, performance can vary significantly by stage.

To address the statistical question, we could directly work with the rank at each stage. However, as we will argue in Section 4, working with this variable leads to many statistical complications. We instead explore variables that are not exactly the rank, but that can be used to determine it and are more amenable to statistical modelling. Figure 1 shows the cumulative time of riders by stage. Cumulative time seems to increase linearly by stage, which suggests that a linear regression model might be appropriate. There are, however, some issues with this variable. First, the variance of the observations increases with stage. This is due to the fact that cumulative time is determined by adding individual stage times. The more times are added, the more variability there will be. Second, the observations are not independent:

clearly a rider's cumulative time has to increase from one stage to the next. This also imposes a non-trivial combinatorial constraint that makes working with cumulative time too complicated.

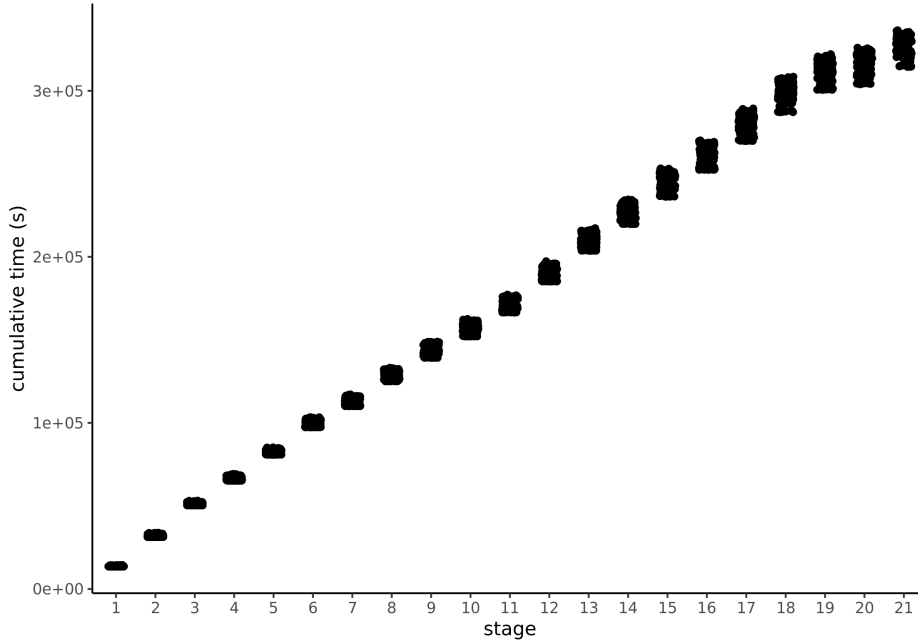


Fig 1: Scatterplot of cumulative time by stage. Each point corresponds to a rider's cumulative time at the corresponding stage.

One alternative to cumulative time is the time difference of every rider to the race leader at every stage. A visual inspection of Figure 2, which shows how time differences vary through stage, suggests a linear relationship between stage and time difference. As was the case of cumulative time, the variance of the time difference also increases with stage—for similar reasons as before. Although time difference also result in a combinatorially complicated structure, it is not nearly as complicated as the one induced by the cumulative time. The model proposed in Section 4 addresses these issues.

4. Statistical methodologies.

5. Conclusion. limitations: - cannot model linear relationship between time difference and stage with log link; this is what might cause over and

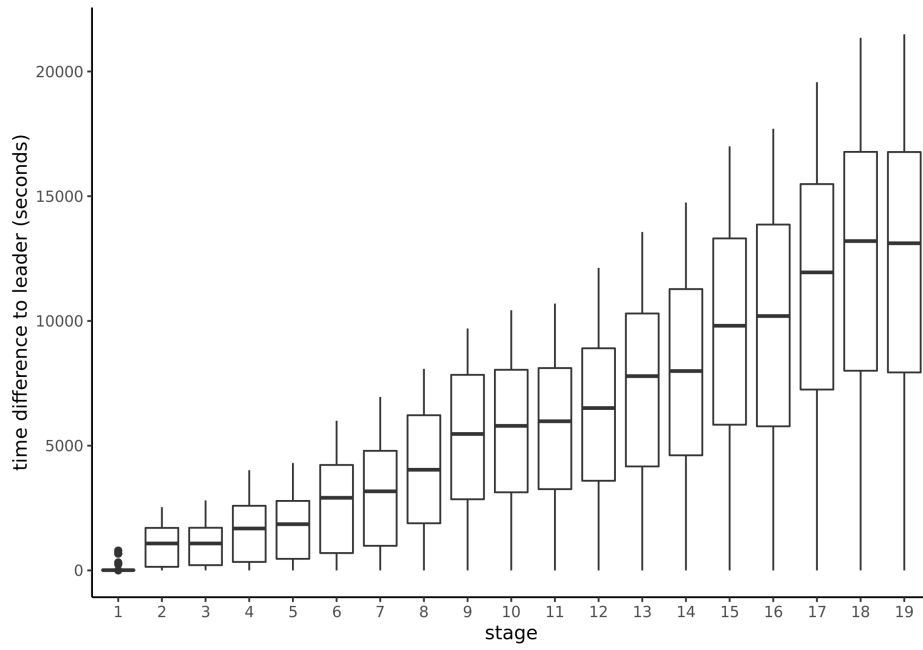


Fig 2: Boxplots of time difference to leader for every stage. The variability in the time difference increases as stages progress.

under estimation -
[Lauderdale \(2012\)](#)

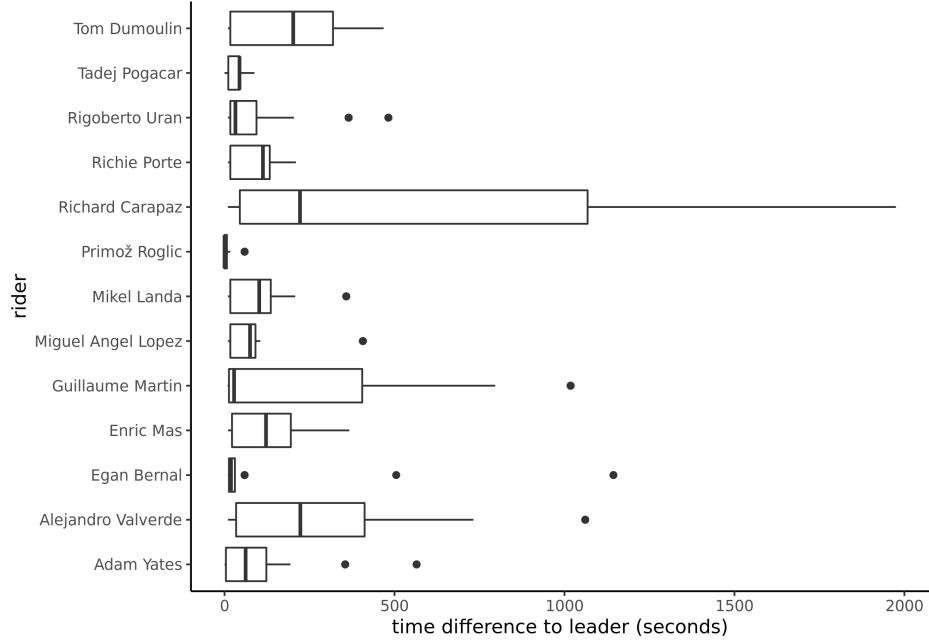


Fig 3: Boxplots of time difference to leader for every top contender. Contenders seem to vary between them, even if they were all contesting the Tour.

Rider	True ranking	Predicted ranking	Predicted probability of winning
Tadej Pogačar	1	2	0.228
Primož Roglič	2	1	0.552
Richie Porte	3	7	0.111
Mikel Landa	4	6	0.112
Enric Mas	5	8	0.095
Miguel Ángel López	6	3	0.182
Tom Dumoulin	7	10	0.052
Rigoberto Urán	8	4	0.159
Adam Yates	9	5	0.152
Damiano Caruso	10	67	<0.0001

TABLE 2

Top 10 riders of the 2020 Tour de France. For each rider, its ranking and predicted ranking are shown, along with the predicted probability of winning.

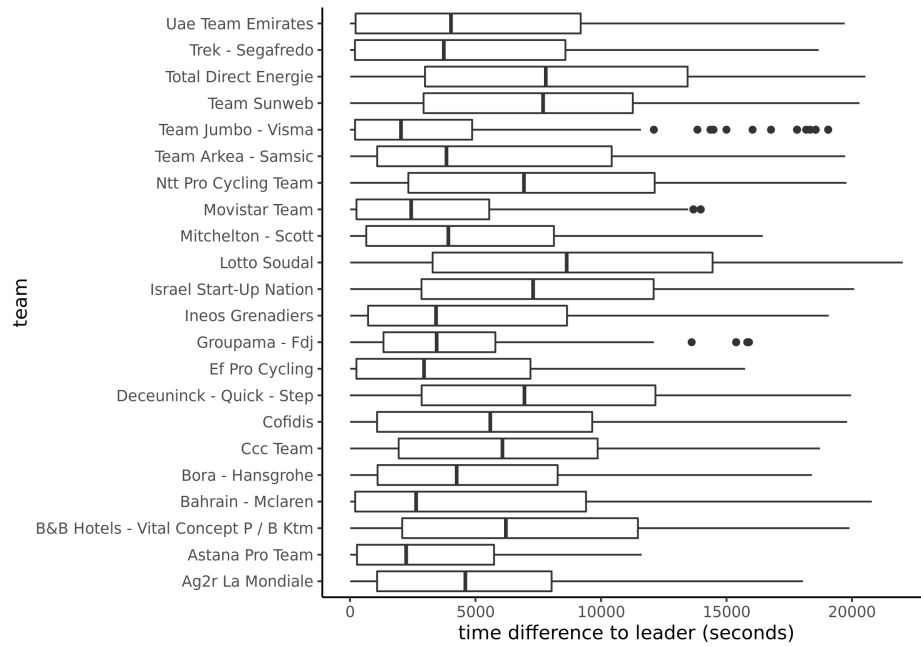


Fig 4: Boxplots of time difference to leader for every team. Contenders seem to vary more between them than teams.

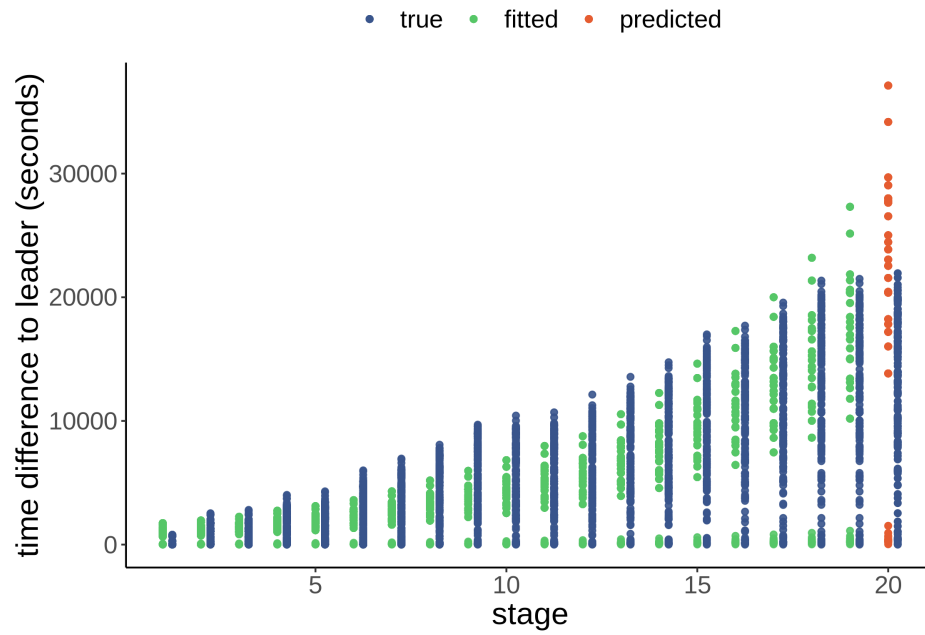


Fig 5: Comparison of fitted and predicted values against the true values. The compound Poisson-Gamma model successfully captures the increasing variability of observations.

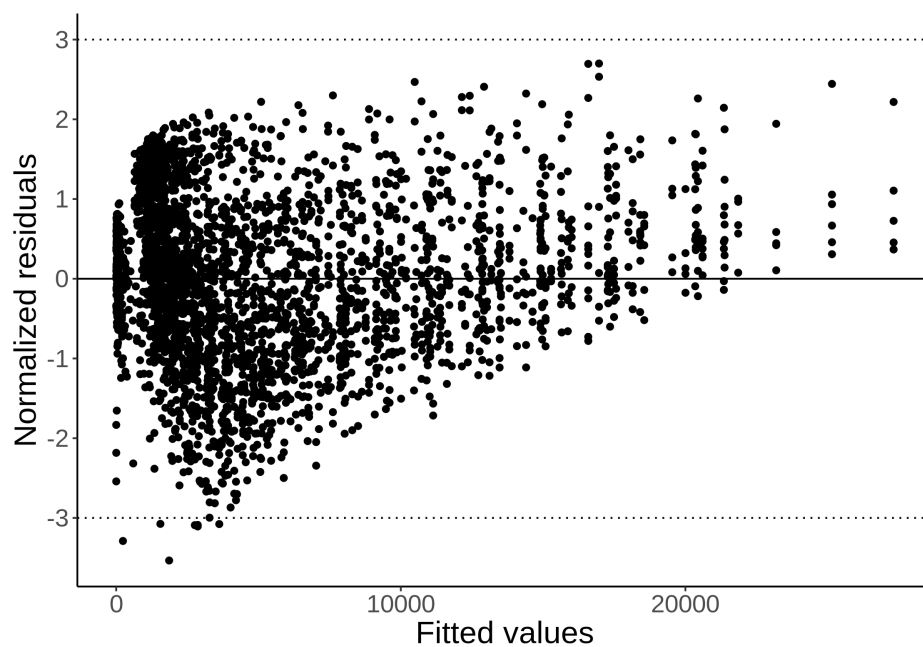


Fig 6: Normalized residuals of the compound Poisson-Gamma model. The vast majority of values are well within the ± 3 bound. The model tends to overestimate when fitted values are small and underestimate when they are large.

References.

LAUDERDALE, B. E. (2012). Compound Poisson—Gamma Regression Models for Dollar Outcomes That Are Sometimes Zero. *Political Analysis* 387–399.

DEPARTMENT OF STATISTICS
UNIVERSITY OF BRITISH COLUMBIA
VANCOUVER, BC, CANADA V6T 1Z4
E-MAIL: gian.diluvi@stat.ubc.ca,