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Literature Review: Modeling Qualifying Performance in Formula 1

Introduction

This literature review explores the academic and economic research on Formula 1, focusing on the roles of drivers, teams, and the measurable technical conditions. In terms of the project, the goal is to build a regression model to predict qualifying lap time using variables such as tire condition, stint number, track temperature, and team. Qualifying sessions offer a unique environment for this kind of analysis because they remove many unpredictable race-day factors and create a better setting to study performance. This review looks at six academic papers, including four from economics journals, to understand what work has already been done, what methods have been used, and how this project contributes something new to the conversation.

Why Qualifying Performance Matters

Several of the chosen articles and papers highlight that qualifying is more than just a setup for the race. It plays a key role in determining how well a driver performs on race day. The Wesselbaum and Owen (2021) article shows that starting from pole position increases the chance of winning by about 10 percent, even when accounting for driver and team strength. Their regression models also show that pole sitters typically finish two places higher than average. This proves that qualifying has real, lasting effects on race outcomes. Because of this, qualifying is worth analyzing on its own and not just as part of the race.

The Fry et al. (2024) article expands on this idea by introducing a model called time-rank duality. The authors show that race time and final position are closely linked and can be used to estimate one another. This means that lap times carry important information about performance, even when full race results are not available. In terms of qualifying, this supports the idea that lap time is a useful outcome to study. Their work justifies using lap time as a dependent variable in a regression model, especially when trying to understand driver and team performance during qualifying.

Separating Driver and Team Influence

A major challenge in performance modeling is separating what the driver controls from what the team and car provide. The Bell et al. (2016) article deals with this by using a multilevel model that analyzes race data from 1950 to 2014. Their findings show that the teams are what explain most of the variation in performance, but drivers matter more in difficult situations like street circuits or wet weather. This suggests that both team and environmental conditions should be included in performance models. For the project, this supports the decision to include team as a predictor when modeling lap time, and to consider how certain variables might matter more under specific conditions.

Eichenberger and Stadelmann (2009) use fixed-effects regression to rank drivers by controlling for team performance and technical problems. They argue that raw results can be misleading because they often favor drivers in better cars. By removing team effects, they show that some historically great drivers outperform others once the car advantage is taken away. This paper provides a direct method for how to control for the team aspect when building regression models. For the project, this could be helpful in trying to isolate how much tire condition or stint affects lap time, separate from which team the driver belongs to.

How Regression Models Can Be Used to Study Performance

Other papers focus more on how performance is modeled. In the Rockerbie and Easton (2021) paper, they use censored regression to analyze how team budgets and driver salaries influence podium finishes. They find that both matters, but the best results happen when a strong driver is paired with a strong car. They also find that spending more eventually has less impact. While this paper is focused on race performance, the idea of interaction is still very relevant. For qualifying, this suggests that a variable like tire freshness might have a bigger or smaller effect depending on the team or stint. It also encourages testing whether some effects change based on context, which this project aims to uncover.

In the Piquero et al. (2021) article, they use a method called group-based trajectory modeling to sort drivers into performance categories based on how many points they earned from 2014 to 2019. They find that drivers tend to fall into consistent performance groups across seasons, such as top-tier, mid-tier, and lower-tier performers. Although their study does not use regression or focus on qualifying sessions, it shows that driver performance can be grouped and analyzed in useful ways using statistics. Their work also points out a gap in the research, which is that many studies focus on race results or full-season outcomes, but few look closely at qualifying sessions. This opens an opportunity to add something new by using regression to predict qualifying lap times with detailed data from individual sessions.

Common Themes and Gaps in the Literature

There are several key ideas that are present in almost all all six articles and papers. First, most studies agree that team performance plays a large role in results, but driver skill still matters. The Bell et al (2016). and Eichenberger and Stadelmann (2009) articles both show that controlling for team is necessary to get an accurate picture of driver performance. In the Rockerbie and Easton (2021) paper, the authors go a step further by showing that a driver's performance depends in part on the team they work with, and that results improve when both are strong. These studies support the use of team as a control variable and suggest looking at how predictors might interact, rather than affect performance on their own.

Secondly, qualifying performance is widely seen as valuable, but very few papers focus directly on qualifying sessions. The Wesselbaum and Owen (2021) and Fry et al. (2024) articles provide strong arguments for why qualifying matters, but most studies focus on race or season outcomes. None of the reviewed articles build regression models using session-level qualifying data from modern seasons. This project helps fill that gap by using detailed data from the 2024 season to study what affects qualifying lap times. It includes information like tire condition, stint number, and track temperature to build a clear model of qualifying performance. This sort of analysis has not been done much in past research.

Finally, all of the papers reviewed use careful statistical methods to account for outside factors and better understand driver performance. Whether through fixed effects, random effects, or other techniques, the goal in each study is to separate a driver's true ability from things like team or race conditions. This project follows a similar idea but focuses on qualifying sessions, where conditions are more consistent, and it is easier to measure pure performance.

Hypotheses and Regression Setup

Research Question and Hypothesis

The research question is: does the performance gap between teams change as tire wear increases during qualifying sessions? The null hypothesis is that the effect of tire wear on lap time is the same for all teams. The alternative hypothesis is that tire wear affects some teams more than others, meaning team-based lap time differences vary depending on tire age. This interaction is the focus of the analysis.

Regression Variables and Justification

The variables remain the same as those from the proposal, with the dependent variable being LapTimeSeconds, which is the driver's qualifying lap time converted to numeric seconds. The independent variables are:

- TyreLife_Log: A log-transformed version of TyreLife, which counts how many laps a tire was used before the flying lap. The log transformation reduces skewness and captures diminishing effects of wear.
- FreshTyre: A binary variable (1 = new, 0 = used) indicating whether the tire was brand new. This controls for the performance boost of fresh tires.
- TrackTemp: The average track surface temperature during the session. It affects tire grip and engine performance.
- Stint: The run number during the session (e.g., first or second attempt), included to control for track evolution effects.
- TyreLife_Log:C(Team): The interaction term used to test whether the effect of tire age varies by team. It allows each constructor to have a different slope for tire degradation.

Interaction Term

The interaction between TyreLife_Log and Team is included using TyreLife_Log:C(Team). This allows the model to estimate a different effect of tire wear on lap time for each team, directly reflecting the research hypothesis.

Data Cleaning and Preparation

The dataset includes qualifying session data from all completed 2024 Formula 1 races, pulled using the FastF1 Python library. Rows with missing data or deleted laps were removed. Deleted laps are typically due to track limit violations or incidents and do not represent the true performance of the car. Lap times were converted into seconds, and FreshTyre was changed from boolean to numeric. Track temperature was calculated as the session average and assigned to each lap. Laps that were longer than 130 seconds were excluded, as they likely represent outliers such as aborted runs, cool-down laps, or laps affected by unusual conditions.

Transformed Variable

To satisfy the transformation requirement, TyreLife was log-transformed. A histogram showed that it was right-skewed, with many drivers using fresh tires and only a few pushing into higher wear levels. The transformation (log(1 + TyreLife)) smoothed this skew and helped better model how lap time increases with wear at a decreasing rate.

Missing Data and Output

Deleted laps and missing values were dropped from the dataset. With over 4,900 qualifying laps remaining, the sample size was large enough for stable estimation. No imputation was required.

Data Analysis, Results and Discussion: Modeling Qualifying Performance in Formula 1

Variance Inflation Factor and Regression Assessment

To test for multicollinearity in the model, variance inflation factor (VIF) statistics were calculated for the main independent variables: FreshTyre, TrackTemp, TyreLife_Log, and Stint.

These were the core numeric variables used in the regression, excluding categorical interaction terms such as Team, which are typically not included in VIF checks due to the way they are encoded. The VIF results were all well below commonly used thresholds, with values as follows: FreshTyre (1.94), TrackTemp (1.01), TyreLife_Log (1.91), and Stint (1.09). Since all values were below 2, there is no evidence of multicollinearity between the predictors. This means the variables are not strongly correlated with each other, and there is no need to adjust the regression model.

The regression was run using qualifying lap data from all completed 2024 Formula 1 races. The dependent variable was LapTimeSeconds, representing each driver's fastest qualifying lap converted to seconds. The model included TyreLife_Log as a key predictor, with an interaction term between TyreLife_Log and Team to test whether tire wear impacts lap time differently depending on the constructor. Other variables included in the model were FreshTyre, TrackTemp, and Stint. The R-squared value of the model was 0.085, meaning the model explains about 8.5 percent of the variation in lap time. Although this number is not high, it is typical for real-world sports performance data where many unobserved factors influence the outcome. The F-statistic was 6.273 with a p-value well below 0.001, indicating that the model as a whole is statistically significant.

The coefficient for FreshTyre was 10.77 and statistically significant at the 1 percent level. This means that, on average, using a fresh tire leads to a lap time that is about 10.77 seconds faster than when using a used tire, holding all else constant. TrackTemp had a negative coefficient of –0.42 and was also statistically significant. This suggests that as the track temperature increases by one degree, lap time tends to decrease slightly, which aligns with expectations that warmer conditions may improve grip.

The coefficient for Stint was 0.30, but this result was not statistically significant ($p = 0.329$). This implies that there is no strong evidence that the run number (i.e., whether the lap was done earlier or later in the session) had a consistent effect on lap time in this model.

The interaction terms between TyreLife_Log and each team were all statistically significant with positive coefficients ranging between 12.6 and 15.4. This indicates that tire wear had a measurable and increasing effect on lap time across all teams, although the strength of the effect varied slightly. For example, Kick Sauber and Williams had coefficients above 15, while Alpine was slightly lower at 12.6. The positive signs mean that as tire wear increases (measured on a log scale), lap time becomes slower, and this effect is consistent across constructors. These results support the idea that teams experience different levels of performance drop-off as tire age increases.

Discussion and Interpretation

The regression model produced several findings that help address the project's central research question: *does the performance gap between teams change as tire wear increases during qualifying sessions?* The results are consistent with the alternative hypothesis, which proposed that tire wear affects some teams more than others, leading to team-based lap time differences that vary depending on tire age. The interaction terms between TyreLife_Log and each team were all statistically significant, meaning that tire age had a measurable impact on lap time, and the strength of this impact differed depending on the constructor. While all teams experienced slower lap times as tire wear increased, some teams saw a slightly larger decline than others.

These results support the hypothesis that tire degradation does not affect all teams equally. Teams like Kick Sauber and Williams had among the highest coefficients, indicating a greater increase in lap time as tires aged, while teams like Alpine showed a smaller, but still significant, increase. This suggests that car setup, tire strategy, or chassis design may influence how much lap time is lost due to wear. Including this interaction term allowed the project to go beyond testing for a general tire effect and instead explore whether team-specific differences existed. This was a key part of the project's original research goal.

The result for FreshTyre was also highly significant, with a positive effect on lap time of over 10 seconds. This matches expectations from Formula 1 strategy and supports the literature that emphasizes the performance gain from fresh tires. In qualifying, even a small gain in grip can lead to a faster lap, so this result is both reasonable and meaningful. Similarly, TrackTemp was statistically significant with a negative coefficient, showing that warmer tracks are generally associated with faster laps. This again aligns with prior findings and real-world racing conditions, where higher track temperatures often help tires reach optimal grip.

On the other hand, the variable for Stint was not statistically significant. While the expectation was that later runs in a qualifying session (e.g., second or third attempts) might be faster due to track evolution, this was not strongly supported by the model. One possible reason could be that in real qualifying conditions, there are tradeoffs such as traffic, red flags, or weather, which may cancel out the positive effect of a more rubbered-in track. Although Stint was included based on theory and prior studies, its lack of significance may point to more complex interactions that could not be captured here.

Compared to the existing research, the results of this project are consistent with the literature in several ways. Most prior studies focus on full-season or race outcomes, but they consistently show that team and tire factors influence driver performance. This project applied similar methods to a more focused question being qualifying lap time and reached aligned conclusions. For instance, studies that used fixed effects to separate driver and team contributions often suggested that car performance explains a major part of the result. This project builds on that by showing that even within one session, team-specific tire degradation effects are visible. It adds to the literature by modeling not just overall lap time but also how lap time changes with tire wear depending on the team.

There were also some new aspects to this project. One was the use of session-level telemetry data through the FastF1 API, which allowed for fine-grained analysis of track temperature, tire status, and stint number. These variables are not typically included in broad performance studies, and they helped improve the detail of the model. Including FreshTyre, for example, led to a clear and strong result that confirmed how much a new tire helps during qualifying. TyreLife was log-transformed to improve its distribution and better model the diminishing returns of each additional lap, which was a useful statistical adjustment that also made practical sense.

Limitations

However, the project had several limitations. First, although the model included nearly 900 laps, the number of observations varied across teams. Some teams completed more qualifying laps than others, which could have influenced the coefficient estimates. Second, not all drivers completed every stint or followed the same tire strategy, introducing variation that could not be fully controlled. Third, the model did not account for several important technical variables like engine mode selection, fuel load, or real-time track evolution, all of which are known to affect lap time. Formula 1 is a highly data-driven sport, where cars are equipped with thousands of real-time sensors that generate a vast array of performance and telemetry data. As a result, many subtle yet impactful factors go unaccounted for in this simplified regression model. Lastly, the R-squared value was relatively low (0.085), which is expected given the complexity of the sport and suggests that a significant portion of lap time variation likely comes from factors not captured in the current dataset, such as driver inputs, setup changes, or aerodynamic effects.

There were no major issues during data collection, though some laps had to be dropped due to missing or deleted data. These included laps where drivers went off track or had times invalidated. This was accounted for during the data preprocessing phase. One potential improvement would be to gather more complete data across the season and possibly expand the analysis to include Q1, Q2, and Q3 session types separately, rather than grouping all qualifying laps together.

Conclusion

Looking ahead, there are several ways to expand this research. Future studies could include sector-level analysis to see where time loss occurs most. They could also include weather variables like humidity or wind, or control for track layout to see if tire degradation has a larger effect on street circuits compared to permanent tracks. It may also be useful to look at qualifying performance changes over a driver’s career or within different rule eras, which could be done with panel data. This project shows that using detailed session-level data can reveal patterns in performance that are not always clear in season-long summaries, and it opens the door to more advanced modeling in motorsport analytics.

Appendix

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                            OLS Regression Results
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Dep. Variable:          LapTimeSeconds   R-squared:                       0.076
Model:                             OLS   Adj. R-squared:                  0.062
Method:                  Least Squares   F-statistic:                     5.743
Date:                 Sat, 03 May 2025   Prob (F-statistic):           3.16e-10
Time:                         22:37:21   Log-Likelihood:                -3846.6
No. Observations:                  928   AIC:                             7721.
Df Residuals:                      914   BIC:                             7789.
Df Model:                           13
Covariance Type:             nonrobust
===========================================================================================================
                                             coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------------------------
Intercept                                 75.4156      5.486     13.747      0.000      64.649      86.182
FreshTyre[T.True]                         12.2435      1.906      6.422      0.000       8.502      15.985
TyreLife_Log:C(Team)[Alpine]              14.5525      2.206      6.595      0.000      10.222      18.883
TyreLife_Log:C(Team)[Aston Martin]        15.9224      2.305      6.908      0.000      11.399      20.446
TyreLife_Log:C(Team)[Ferrari]             15.7268      2.171      7.243      0.000      11.466      19.988
TyreLife_Log:C(Team)[Haas F1 Team]        15.6439      2.387      6.554      0.000      10.959      20.329
TyreLife_Log:C(Team)[Kick Sauber]         16.2966      2.601      6.266      0.000      11.193      21.401
TyreLife_Log:C(Team)[McLaren]             15.6409      2.301      6.797      0.000      11.125      20.157
TyreLife_Log:C(Team)[Mercedes]            16.3606      2.149      7.613      0.000      12.143      20.578
TyreLife_Log:C(Team)[RB]                  16.1003      2.463      6.537      0.000      11.267      20.934
TyreLife_Log:C(Team)[Red Bull Racing]     16.7395      2.296      7.291      0.000      12.234      21.245
TyreLife_Log:C(Team)[Williams]            17.7653      2.486      7.148      0.000      12.887      22.643
TrackTemp                                 -0.2357      0.107     -2.193      0.029      -0.447      -0.025
Stint                                      0.5648      0.326      1.734      0.083      -0.074       1.204
==============================================================================
Omnibus:                        33.386   Durbin-Watson:                   2.935
Prob(Omnibus):                   0.000   Jarque-Bera (JB):               19.919
Skew:                            0.207   Prob(JB):                     4.73e-05
Kurtosis:                        2.413   Cond. No.                         488.
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*OLS Regression Results: Had a talk with Professor Jess regarding this on Thursday. This is the updated regression result (this was the actual one that was meant to be in the appendix of part 1).

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Final VIFs:
        Feature       VIF
0     TrackTemp  1.006527
1  TyreLife_Log  1.873689
2     FreshTyre  1.898751
3         Stint  1.081459
```