
A State-Space Approach to Modeling Tire Degradation in Formula 1 Racing

arXiv Preprint
XX(X):1-18
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DOI: 10.1177/ToBeAssigned
www.sagepub.com/



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Abstract

Tire degradation plays a critical role in Formula 1 race strategy, influencing both lap times and optimal pit-stop decisions. This paper introduces a Bayesian state-space modeling framework for estimating the latent degradation dynamics of Formula 1 tires using publicly available timing data from the FastF1 Python API. Lap times are modeled as a function of fuel mass and latent tire pace, with pit stops represented as state resets. Several model extensions are explored, including compound-specific degradation rates, time-varying degradation dynamics, and a skewed t observation model to account for asymmetric driver errors. Using Lewis Hamilton's performance in the 2025 Austrian Grand Prix as a case study, the proposed framework demonstrates superior predictive performance over an ARIMA(2,1,2) baseline, particularly under the skewed t specification. Although compound-specific degradation differences were not statistically distinct, the results show that the state-space approach provides interpretable, probabilistic, and computationally efficient estimates of tire degradation. This framework can be generalized to multi-race or multi-driver analyses, offering a foundation for real-time strategy modeling and performance prediction in Formula 1 racing.

1 Introduction

One of the most important factors contributing to race strategy in a Formula 1 Grand Prix is tire degradation. As tires degrade throughout the course of a race, drivers are forced to go slower. As such, it can be beneficial to enter the pit lane for a new set of tires. However, drivers lose time relative to their competitors while they are waiting for new tires to be put on. In this way, deciding to make a pitstop is a delicate balance, and can easily affect a competitor's results. A

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dramatic example of this occurred during the 2024 Italian Grand Prix, in which Charles Leclerc of Ferrari beat Oscar Piastri of McLaren (Giles, 2024). Leclerc only stopped once for new tires, while Piastri—who was leading the race and on track to win—made a second pitstop later in the race that cost him victory. By stopping early for a set of “hard” tires and continuing till the end of the race, Ferrari was able to beat their opponent even though their car was generally slower than the McLaren throughout that weekend.

In each Formula 1 grand prix, there are three different dry tire compounds for teams to choose from, along with an intermediate tire and a full wet tire for rainy conditions. The dry tires—referred to as “hard”, “medium”, and “soft”—are designed by tire manufacturer Pirelli to degrade at different rates (Pirelli, n.d.). Tire degradation itself is a phenomenon which occurs as a result of the extreme forces put through the tires during a grand prix. These forces cause shearing of the rubber from the surface of the tire and thermal degradation of the tire carcass due to friction (Farroni et al., 2016). Softer tires provide more grip initially and allow for faster lap times. However, they degrade faster than harder tires, which leads to slower lap times and a need to pit sooner. On the other hand, harder tires are not as quick, but degrade more slowly. Therefore, a driver can typically do more laps at a reasonable pace on a harder tire.

As tires wear, lap times tend to increase throughout a stint (a set of laps completed on a single set of tires). Because replacing degraded tires can yield faster overall race times, strategists must balance tire longevity against short-term performance. Predictive models of degradation can help answer questions such as “How rapidly do lap times deteriorate?” or “When does degradation become performance-limiting?” In live racing, models must also be interpretable and computationally efficient enough to inform real-time decisions. To address this, we propose a Bayesian state-space model that represents tire degradation as a latent process observed indirectly through lap times.

To the best of our knowledge, there are no examples in the literature that apply state-space models to the phenomenon of tire degradation in Formula 1. While prior research (e.g., Todd et al., 2025) has explored deep learning approaches for tire energy prediction, those methods often lack interpretability and explicit uncertainty quantification—features that are crucial in operational race environments. Because of this, we believe that state space models could be an asset to F1 teams looking to gain an edge in predictive modeling.

Using publicly available data from the FastF1 Python API (Oehrly, 2025), we analyze Lewis Hamilton’s race at the 2025 Austrian Grand Prix. Lap times are modeled as a function of fuel mass and latent tire pace, with pit stops treated as state resets. Several extensions of the model are tested, including compound-specific degradation rates and time-varying degradation dynamics, with performance evaluated via cross-validation. We use a Bayesian workflow for model development, visualization, and comparison to allow for easier model implementation and parameter interpretation.

The results show that the Bayesian state-space model fits lap-time data well and outperforms an ARIMA(2,1,2) baseline in predictive accuracy. We find limited evidence of statistically distinct degradation rates between the hard and medium compounds in this case study—likely due to a lack of data and modern tire management practices, where drivers target consistent lap times

to control wear. However, the model nevertheless provides interpretable, real-time estimates of degradation and uncertainty, offering a practical foundation for strategy modeling even when compound effects are subtle.

Although presented for a single race, the framework generalizes naturally to multi-race or multi-driver analyses, making it a promising tool for quantifying degradation dynamics, evaluating strategies, and improving model interpretability. In the remainder of this paper, we will describe the dataset and processing steps taken to obtain the time series of interest. Then, we will provide a brief background on state-space models and describe the various models we propose for analysis in this paper. Lastly, we perform model selection and assessment, and discuss the results of fitting each model.

2 Data

The FastF1 Python API (Oehrly, 2025) provides access to a vast array of data pertaining to each F1 grand prix. Of interest to us are the individual lap times for each driver, what tire compound the driver used on each lap, and on what laps the driver pitted for a new set of tires. Although there is much more available in the API, the aforementioned items will be sufficient for the scope of this paper.

Figure 1 contains a plot illustrating the time series that we selected for analysis in this paper. We chose Lewis Hamilton’s race at the Austrian Grand Prix because his race was fairly uneventful. No safety car was deployed and he spent much of the race alone in free air, unimpeded by slower vehicles. Data cleaning was minimal, consisting only of the removal of laps in which the driver entered or exited the pit lane, because such lap times would impart little to no information about degradation.

Lastly, we include the amount of fuel in kilograms for the driver at each lap as a covariate in our model. This data did not come from the FastF1 Python API, and is assumed to start at 110 kilograms on lap 1 and decay linearly to zero by the last lap. 110 kilograms is assumed to be the starting value since that is the maximum allowed by regulation. While a driver may start the race with less than 110 kilograms of fuel, it is reasonable to assume that there is very little fuel left at the end of the race because engineers try to optimize this as much as possible to increase performance.

3 Bayesian State-Space Model

In this section we’ll first briefly review state space models, then describe in detail the process used to model latent degradation rates through the observable lap time process. All models were fitted using the software package Stan (Stan Development Team, 2020).

3.1 Background

State-space models (SSMs) are a popular modeling framework for time-series data due to their flexibility. They have found applications in a wide range of areas, from ecological time series (Auger-Methe et al., 2021), to financial data (Zeng and Wu, 2013), to sports analytics. Within

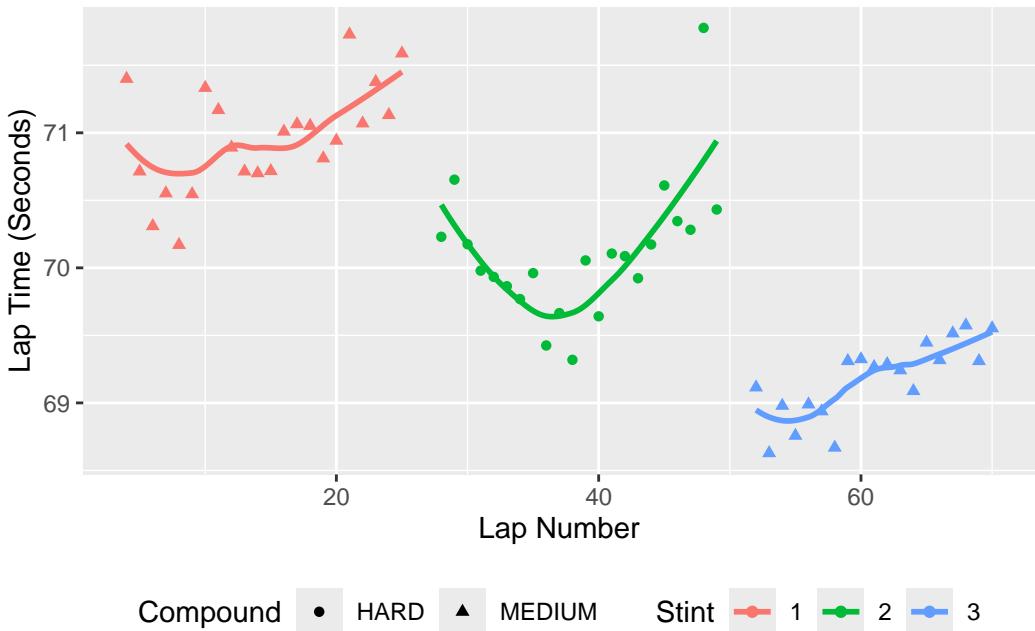


Figure 1. Tire Degradation for Lewis Hamilton during the Austrian Grand Prix. We can see a subtle but noticeable increase in lap times throughout the course of each stint. In the second stint on the hard tires, we can also see a warm-up period from laps 28 to 38.

realm of sports analytics, Ridall et al. (2025) used a Bayesian state space model to predict Premier League football match outcomes by assigning a latent state to the attacking and defending strengths of each team. Duffield et al. (2025) also introduced new approaches for skill rating in competitive sports based on SSMs.

The defining feature of SSMs is their ability to model both a latent unobserved time series via a state equation $\alpha_t \sim \pi(\cdot | \alpha_{t-1}, y_{1:t-1})$, and an observation time series $Y_t | \alpha_t \sim f(\cdot | \alpha_t)$ that consists of measurements which are related to the latent process. SSMs generally make two assumptions:(1) the latent time series evolves as a (typically first order) Markov Process and (2) the observations are independent of one another when we condition on the latent states.

A variety of methods exist for estimation and inference, including the Kalman filter for linear-Gaussian models (Kalman, 1960), Sequential Monte Carlo methods for nonlinear or non-Gaussian systems, and particle MCMC for joint inference on states and parameters (Andrieu, Doucet, and Holenstein 2010). This paper uses Stan and MCMC (Auger-Méthé et al., 2021) for model fitting and posterior sampling due to its flexibility and ease of implementation.

3.2 Base Model Specification and Parameter Interpretation

We start with the observation equation for a driver's lap times:

$$y_t = \alpha_t + \gamma * fuel_t + \epsilon_t \quad (1)$$

$$\epsilon_t \sim N(0, \sigma_\epsilon^2) \quad (2)$$

Here y_t represents the observed lap time for the driver on lap t . α_t represents the true latent pace of the tires after accounting for fuel and degradation. $fuel_t$ is a covariate that represents the derived amount of fuel in kilograms for the driver on lap t , and γ is the estimated increase in lap time due to an additional kg of fuel. Lastly, ϵ_t accounts for errors that would result in a lap time being different from α_t after accounting for fuel loss. Possible sources of this error include driver mistakes and the presence of other cars.

Now we present the process equation:

$$\alpha_{t+1} = (1 - I_{pit_t})(\alpha_t + \nu) + I_{pit_t}(\alpha_{reset}) + \eta_t \quad (3)$$

$$\eta_t \sim N(0, \sigma_\eta^2) \quad (4)$$

where:

$$I_{pit_t} = \begin{cases} 1 & \text{if driver has a new set of tires on lap } t+1 \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

$$t \in \{1, 2, \dots, T\} \quad (6)$$

As mentioned earlier, the latent states α_t represent the true pace (or lap time) that the tire is capable of. In the most basic version of the model, we consider a linear rate of decay in lap times, represented by the static parameter ν in the model. However, we allow for error in this decay process by including the term η_t . Perhaps most interesting in the process equation is the inclusion of an indicator variable for pit stops. These allow us to reset the degradation process to α_{reset} after the driver puts on a new set of tires, and then continue the degradation process as normal afterwards.

3.3 Extensions of the Basic Model

We will propose three extensions to this basic model. The first is to estimate different degradation rates for each tire compound, and the second is to allow the degradation rate ν to increase over time. The final extension will explore the benefits of using a skewed t distribution to model the observation errors.

3.3.1 Extension 1 - Compound Specific Degradation As mentioned earlier, Formula 1 tires are designed to degrade at different rates by Pirelli (Pirelli, n.d.). Therefore, a natural first extension to make to the base model is to estimate different degradation rates for each compound. With this in mind, our process equation becomes:

$$\alpha_{t+1} = (1 - I_{pit_t})(\alpha_t + \nu[compound_t]) + I_{pit_t}(\alpha_{reset}[compound_t]) + \eta_t \quad (7)$$

$$\eta_t \sim N(0, \sigma_\eta^2) \quad (8)$$

where:

$$compound_t = \begin{cases} 1 & \text{if hard compound tires are used on lap t} \\ 2 & \text{if medium compound tires are used on lap t} \\ 3 & \text{if soft compound tires are used on lap t} \end{cases} \quad (9)$$

As mentioned above, the main thrust of this extension is to estimate different degradation rates and reset points for each tire compound used by the driver.

3.3.2 Extension 2 - Time-Varying Degradation When tires degrade, there is a loss of mechanical grip as rubber is torn from the surface of the tire. One might well expect that this loss of grip could lead to increased sliding and therefore a compounding of degradation over time. With this in mind, we propose for the second extension a model in which the degradation rate itself increases over time. Under this extension, our process equations become:

$$\alpha_{t+1} = (1 - I_{pit_t})(\alpha_t + \nu_t) + I_{pit_t}(\alpha_{reset}[compound_t]) + \eta_t \quad (10)$$

$$\nu_{t+1} = (1 - I_{pit_t})(\nu_t + \beta[compound_t]) + I_{pit_t}(\nu_{reset}) \quad (11)$$

$$\eta_t \sim N(0, \sigma_\eta^2) \quad (12)$$

The most important difference here is that the degradation rate ν_t now changes with time. We estimate a parameter $\beta[compound_t]$ for each tire compound that represents an additive increase to the degradation rate that occurs at each time step. It is also important to note that since the degradation rate ν_t is allowed to vary with time, we must also include a reset parameter ν_{reset} so that the degradation rate can reset after a pit stop.

3.3.3 Extension 3 - Skewed T Distribution Our final extension to the base model is to use a skewed t distribution (Hansen, 1994) for the observation error. Since drivers are given target lap times by their engineers throughout the race, we expect to observe extreme values predominately in the positive direction. For instance, a driver might make a mistake that could lead to an increase of several tenths of a second in lap time, but then return to the target times given by the

team. A positively skewed t distribution would capture the possibility of extreme values in the positive direction. The base model would have the same process equation, but the observation equation becomes:

$$y_t = \alpha_t + \gamma * fuel_t + \epsilon_t \quad (13)$$

$$\epsilon_t \sim Skewed - T(0, \sigma_\epsilon^2, \lambda, 2) \quad (14)$$

where zero is the mean, σ_ϵ^2 is again the variance, λ is a skewness parameters that ranges from -1 to 1 , and 2 is the degrees of freedom.

Because of the skewed t distribution's heavy tails (with lower degrees of freedom), this model should be more robust to outliers than those using normally distributed errors.

3.4 Discussion of Priors

In general, we lean on moderately strong priors since we are relatively data poor and have ample information to inform priors. Further, informative priors improve convergence stability and speed, making the model more practical in race conditions.

It should also be noted that lap times often differ by mere tenths of a second. Therefore, priors which at first glance appear very strong, are only moderately so. Given lap times vary by ~ 0.5 s per stint, priors with SD = 0.1 represent plausible but informative uncertainty levels.

3.4.1 Base Model The priors for our base model are:

$$\sigma_\epsilon \sim N^+(.3, .1^2) \quad (15)$$

$$\sigma_\eta \sim N^+(.1, .1^2) \quad (16)$$

$$\nu \sim N^+(.05, .1^2) \quad (17)$$

$$\alpha_{reset} \sim N(69, .1^2) \quad (18)$$

We use a relatively strong prior on the observation standard errors σ_ϵ and σ_η because the degradation process should have less error than the observation process. The observation process can be affected by driver inconsistencies. Meanwhile the underlying degradation process should remain relatively consistent throughout.

We also use a half-normal prior on the degradation rate to restrict it to be positive, as a negative overall degradation rate would be nonsensical (if the degradation rate is not allowed to change with time as in extension 3). We centered the prior at .05 since the scale of the data indicates the degradation rates will be small, but we still believe that the degradation rate should be greater than zero.

Lastly, the prior on the α_{reset} parameters are decided by the long runs done during the free practice sessions. Before the race, Lewis Hamilton's teammate Charles Leclerc drove a long-run on medium tires suggesting that the race pace of the medium tires would be roughly 69-69.5 seconds per lap. As such, we centered the α_{reset} prior on 69.

3.4.2 Extension 1 - Compound Specific Degradation The error standard deviation priors for the compound specific degradation model remain the same as before. However, the degradation rate and state resets change since we have to estimate parameters for each tire compound. We have the following extra priors in place of the ν and α_{reset} of before:

$$\nu[1] \sim N^+(.01, .1^2) \quad (19)$$

$$\nu[2] \sim N^+(.03, .1^2) \quad (20)$$

$$\nu[3] \sim N^+(.05, .1^2) \quad (21)$$

$$\alpha_{reset}[1] \sim N(69.5, .1^2) \quad (22)$$

$$\alpha_{reset}[2] \sim N(69, .1^2) \quad (23)$$

$$\alpha_{reset}[3] \sim N(68.5, .1^2) \quad (24)$$

Here $\nu[1]$ is the degradation rate for the hard tire, $\nu[2]$ is the degradation rate for the medium tire, and $\nu[3]$ is the degradation rate for the soft tire. A similar pattern follows for the reset parameters. Here, the priors for the degradation rates and resets reflect our prior beliefs that harder tires should degrade more slowly, but also start out slower. In contrast, the soft tires will start out faster but degrade more quickly.

As mentioned in the previous section, there is data from the second free practice session of that race weekend which suggested that the race pace of the medium tires would be 69-69.5 seconds per lap. We use the lower end of this spectrum to account for greater incentive to do faster lap times during the actual race. Then, we make the hard tire reset value a half second slower—and the soft tire a half second faster relative to the medium tires—to reflect our beliefs that the soft tires will start out faster and the hard tires will start out slower.

3.4.3 Extension 2 - Time-Varying Degradation Here, the error standard deviation priors are the same as the base model, and the reset parameters are the same as for the compound specific degradation model. The main difference is that the degradation priors are now on β , and we include a prior for the degradation state reset ν_{reset} .

$$\beta[1] \sim N^+(.005, .1^2) \quad (25)$$

$$\beta[2] \sim N^+(.01, .1^2) \quad (26)$$

$$\beta[3] \sim N^+(.02, .1^2) \quad (27)$$

$$\nu_{reset} \sim N(0, .1^2) \quad (28)$$

3.4.4 Extension 3 - Skewed T Distribution For the final extension, we have only updated the observation equation. We let σ_ϵ have the same prior as in the base model and put the following prior on the skew parameter λ :

$$\lambda \sim N(.5, .1^2)$$

This prior reflects our belief that the distribution is skewed positively. In fitting the model we used a parameterization of the skewed t distribution in which λ —the skewness parameter—can only take on values between -1 and 1 . This is reflected in the parameter bounds of the Stan code used to fit the model.

Finally, we do not use a prior on the degrees of freedom because we know that outliers can occur due to driver mistakes or getting stuck behind a slower car, and therefore there is a need for heavy tails. Furthermore, we want the model to fit quickly enough that it can provide strategic information during a race. Adding a prior on the degrees of freedom would make the model take longer to run with little added benefit.

4 Results

In this section we will discuss the results of fitting the various models. In particular, we will discuss estimates of degradation rates across tire compound and prediction of lap times.

4.1 Model Selection

We used rolling-origin-recalibration cross validation to perform model selection (Tashman 2000). We describe the cross validation scheme below. Let S_i represent the last lap of stint i , and let $i \in \{1, \dots, N\}$ where N is the number of stints in the race. Lastly, note that $\lceil x \rceil$ represents the ceiling function for some $x \in \mathbb{R}$. We used the following cross validation scheme:

Stint 1

Fold 1 - Train: $[1, 2, \dots, \lceil \frac{3}{4}S_1 \rceil]$ Test: $[\lceil \frac{3}{4}S_1 \rceil + 1]$

Fold 2 - Train: $[1, 2, \dots, \lceil \frac{3}{4}S_1 \rceil, \lceil \frac{3}{4}S_1 \rceil + 1]$ Test: $[\lceil \frac{3}{4}S_1 \rceil + 2]$

...

Fold $\frac{S_1}{4}$ - Train: $[1, 2, \dots, S_1 - 1]$ Test: $[S_1]$

...

Stint N

Fold 1 - Train: $[1, 2, \dots, \lceil \frac{3}{4}S_N \rceil]$ Test: $[\lceil \frac{3}{4}S_N \rceil + 1]$

Fold 2 - Train: $[1, 2, \dots, \lceil \frac{3}{4}S_N \rceil, \lceil \frac{3}{4}S_N \rceil + 1]$ Test: $[\lceil \frac{3}{4}S_N \rceil + 2]$

...

Fold $\frac{S_N}{4}$ - Train: $[1, 2, \dots, S_N - 1]$ Test: $[S_N]$

In this way we perform cross validation on each stint of the driver's race, and calculate the root mean squared predictive error for each stint so that we can analyze model performance at the stint-level. Letting \hat{y}_j denote our prediction for the j th lap, our test statistic is then:

$$RMSP_{i,j} = \sqrt{\frac{1}{S_i - \lceil \frac{3}{4}S_i \rceil} \sum_{j=\lceil \frac{3}{4}S_i \rceil}^{S_i} (y_j - \hat{y}_j)^2}$$

We performed cross validation for the base model described above and the three extensions. In addition, we include an ARIMA(2,1,2) model as a baseline. The first-order differencing removes the non-stationary degradation trend, while the AR(2) and MA(2) components capture short-term autocorrelation and transient shocks in lap times. This specification provides a flexible classical time-series benchmark against which to evaluate the state-space models." Results can be seen in Table 1.

Table 1. Cross Validation Results - RMSPE

	ARIMA(2,1,2)	Base Model	Extension 1	Extension 2	Skewed T Dist.
Stint 1	0.613	0.358	0.355	0.386	0.325
Stint 2	0.727	0.673	0.692	0.670	0.601
Stint 3	0.180	0.139	0.140	0.163	0.156
Total	1.520	1.169	1.187	1.218	1.082

Since we obtained samples from the one step ahead predictive distributions using Stan, we also use the Continuous Rank Probability Score (Matheson and Winkler, 1976) with the same cross validation scheme as above to evaluate our probabilistic forecasts. Let $CRPS_{i,j}$ denote the CRPS for the j th lap in the i th stint. The overall CRPS for the stint is:

$$CRPS_i = \frac{\sum_{j=\lceil \frac{3}{4}S_i \rceil}^{S_i} CRPS_{i,j}}{S_i - \lceil \frac{3}{4}S_i \rceil}$$

In other words, we take the average of each CRPS within a stint to get a stint-level CRPS. Similarly, the overall $CRPS$ is an average of each stint-level CRPS. The results can be seen in Table 2. Note that a smaller CRPS is indicative of a better forecast.

Table 2. Continuous Rank Probability Score

	Base	Extension 1	Extension 2	Skew-T	ARIMA(2,1,2)
Stint 1	0.201	0.201	0.220	0.184	0.424
Stint 2	0.377	0.391	0.396	0.316	0.411
Stint 3	0.112	0.115	0.119	0.106	0.137
<i>CRPS</i>	0.230	0.236	0.245	0.202	0.324

The SSM with skewed t errors is shown to be the best in terms of RMSPE, beating the base model by nearly a tenth. Given the scale of the data, this indicates that the skewed t model performs best on out-of-sample data. Interestingly, this model performs much better than the others in the second stint where there is an extreme outlier in the positive direction. Since performance of the state space models is close among those with normal errors we will still examine them all in the remaining sections, but for out-of-sample prediction we deem the SSM with skewed t errors to perform best.

We see a similar pattern in the Continuous Rank Probability Scores (CRPS) for each of the models (Table 2). The skewed t model beats the other models in all stints, but again performs particularly well in stint 2. The CRPS takes into account the full forecast distribution, so forecasts for the skewed t model are likely able to capture extreme values that the normally distributed models are unable to.

4.2 Model Assessment

We obtained posterior samples for the state-space models via Hamiltonian Monte Carlo sampling with 4 chains of 15000 samples each after 15000 burn-in iterations. R-hat values for all parameters were less than 1.01, indicating adequate convergence.

It can be seen from Figure 2 that the models all fit the data reasonably well, and are fairly similar. Notably however, the skewed t distribution is not nearly as affected by outliers in the first and second stints, leading to a better fit.

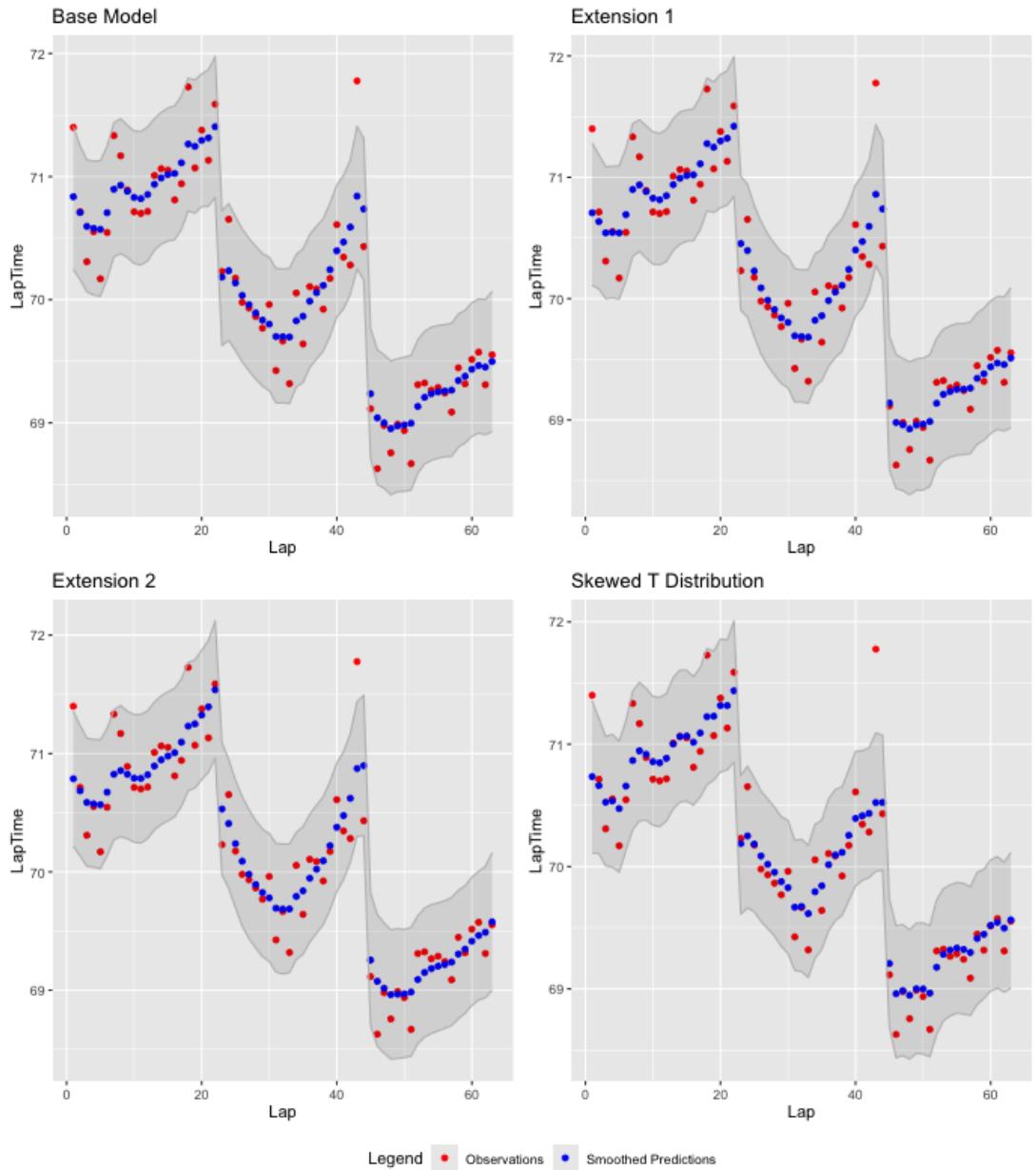


Figure 2. Fit of the various models with 90% credible intervals. The smoothed predictions are based on the entire time series, as opposed to one-step-ahead predictions which are based solely on observations that occur before the prediction. The smoothed predictions are a basic check that show the model fits the data well. Interestingly, we can see that the skewed t model is not nearly as affected by the outlier on lap 43.

4.3 Fitting the First and Second Extensions of the Base Model

In the previous section we saw that the skewed t model performed best. While we did expect this model to perform better than the base model, it is surprising that the compound-specific and time-varying degradation models were outperformed by the base model, especially considering that the entire purpose of having different tire compounds in F1 is so that certain compounds will degrade more quickly.

Table 3. Estimated Degradation Rates with 95% Credible Intervals

	ν	2.5%	97.5%
Hard	0.054	0.004	0.133
Medium	0.060	0.009	0.120

Table 3 shows the estimated values of ν for the first extension to the base model. These estimates are for the hard and medium tires used by Lewis Hamilton in the Austrian Grand Prix, along with bounds for a 95% credible interval. Based on this model, we estimate that Lewis Hamilton loses 5.4 hundredths of a second per lap and 6 hundredths of a second per lap due to tire degradation for hard and medium compound tires respectively, with large uncertainty.

While we do estimate a slightly higher degradation rate for the medium compound tires, the credible intervals have a large degree of overlap, indicating that the data provides little evidence that there is a difference in degradation rate between the compounds.

Table 4. Estimated β with 95% Credible Intervals

	β	2.5%	97.5%
Hard	0.011	0.003	0.020
Medium	0.010	0.002	0.018

From Table 4 it can be seen that the estimated β of the second extension to the base model for the hard tire compound is slightly greater than that for the medium tire compound. Once again however, the credible intervals show a large degree of overlap, indicating little evidence based on the data that the two parameters are different.

Interestingly, the degradation rate ν starts negative, then increases to roughly .175 before a pit stop (see figure 3). This makes sense given that the tires require a warm up period before reaching their optimum operating window(Kelly and Sharp, 2012). Thus, while the skewed t model performed best in terms of predictive accuracy, we can still glean interesting insights from the more complicated models.

Of course, in both model extensions we see that our degradation estimates do not meaningfully change across the tire compounds used. This is likely why the base model performs better in terms of prediction than our extensions. Another important consideration is that drivers strive

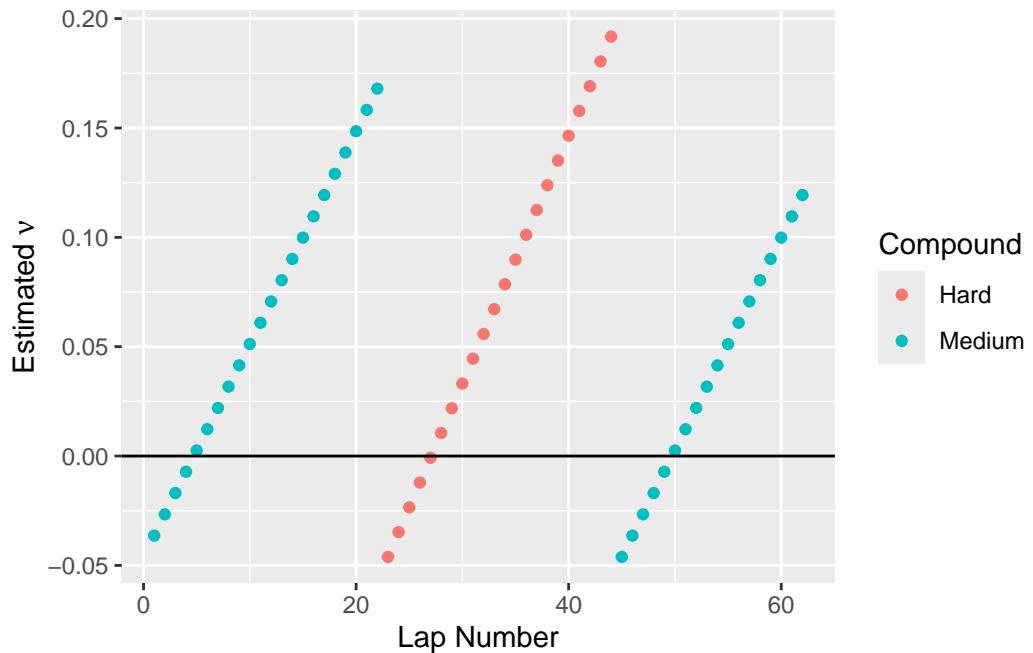


Figure 3. Degradation rates for each lap as estimated by the time-varying degradation model. Interestingly, the degradation rate begins below zero in each stint, indicating the model is capable of capturing a warm-up period for the tires before they begin degrading.

to achieve target lap times set by their engineers during a race. Thus, they are not driving at the absolute limit and are actively trying to manage their degradation rates. This partly explains why we tend to see a linear decay. That being said, each stint only has around 20 laps, so we don't have much data to differentiate what would likely be a small effect size.

4.4 Prediction of Lap Times with Uncertainty

One benefit of these models is the ability to quickly assimilate new data points and get predictions for the next lap time with uncertainty intervals. For example, if we run the base model on laps 1-43 to predict lap 44, we get the results seen in figure 4.

Figure 5 also supports our claim that the models do a good job at forecasting the next lap time. It takes between 15 and 30 seconds to run the base and extension 1 models, giving plenty of time to use the results for decision making in the rest of a lap. In addition, if the fully extended model with increasing degradation rate ν is used, a team could use a certain threshold of ν beyond which they consider a pit stop. In other words, when the degradation rate gets too high, teams can begin seeking an optimal window in which the driver can be pitted. Furthermore, teams could use these results to compare strategies and determine the effects of pitting in optimizing their overall race time.

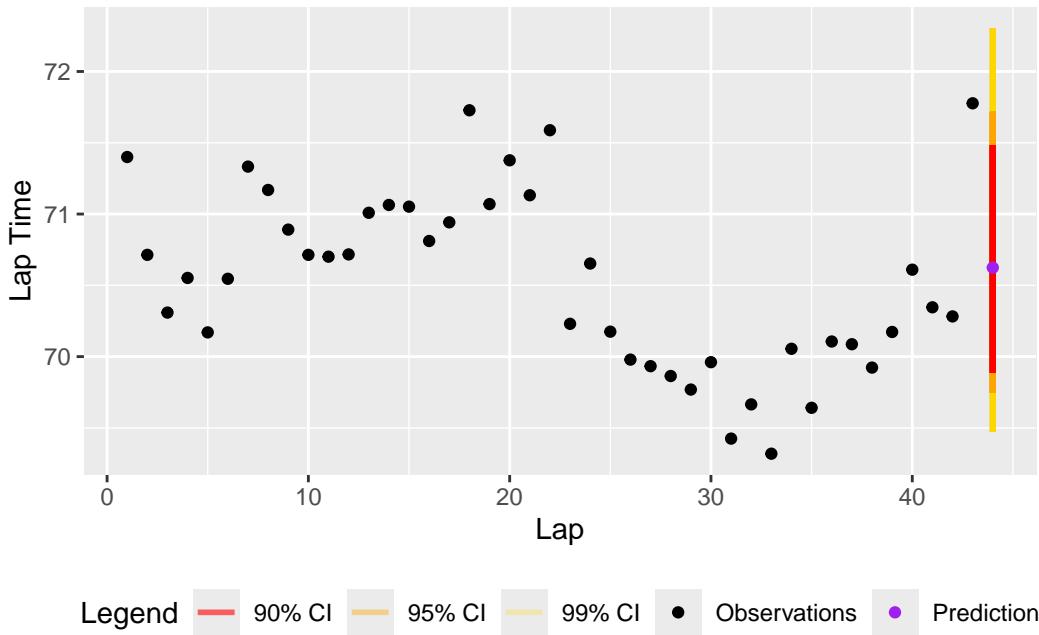


Figure 4. One-step-ahead prediction of lap 44, given laps 1 to 43. Our point estimate is clearly robust to the outlier on the previous lap. We can also see evidence of the skewed t observation errors in the credible intervals. While the 90% interval appears fairly symmetric, we see that increasing the probability extends the interval farther in the positive direction than in the negative direction (relative to the point estimate).

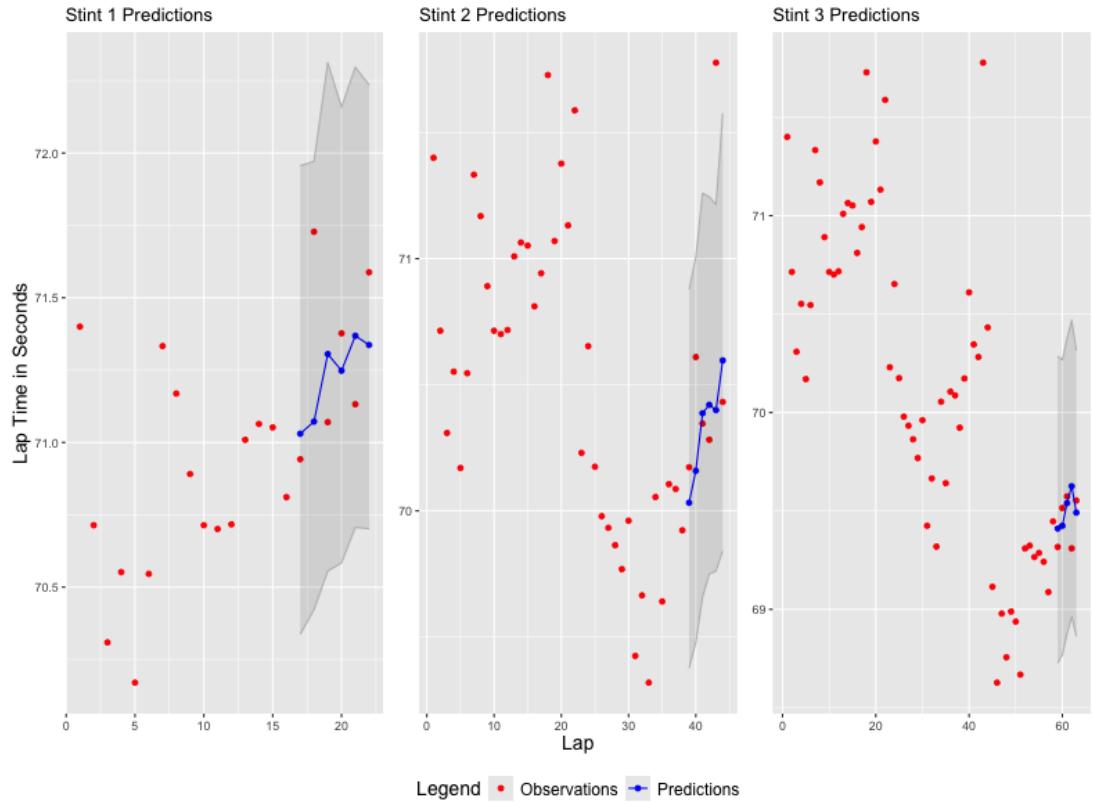


Figure 5. One step ahead predictions with 90% credible intervals for the skew t model. Generally speaking, the models do a good job of predicting the next lap time. The uncertainty intervals almost always contain the observation.

4.5 Limitations and Considerations

Firstly, the Austrian Grand Prix did not have a safety car. Safety cars come onto the track when there has been a serious crash, and all drivers are forced behind the safety car to limit their speeds. As such, driving under safety car conditions drastically reduces degradation since the drivers are limited to much slower speeds. Such a situation could be easily accounted for by extending our model to suspend the degradation process for laps done under safety car conditions.

Secondly, Lewis Hamilton's drive at the Austrian Grand Prix was fairly uneventful and so he was minimally impeded by the drivers ahead. If a driver gets stuck behind a slower car, this can cause an *artificial* increase in lap times that isn't due to tire degradation. The easiest way to address this if necessary is to add a covariate to the observation equation for the distance to the driver ahead. Future work, however, will likely look into more sophisticated ways to address this,

such as a multivariate time series with all drivers and dependent errors based on the distance to the driver ahead.

5 Conclusion

This paper introduced a Bayesian state-space framework for modeling tire degradation in Formula 1 racing, demonstrating that such models can capture the latent deterioration of tire performance while providing interpretable and probabilistic predictions of lap times. Using Lewis Hamilton's 2025 Austrian Grand Prix as a case study, the proposed approach showed superior predictive performance relative to an ARIMA(2,1,2) baseline, particularly when observation errors were modeled with a skewed t distribution to account for asymmetric driver mistakes.

Although degradation rates between tire compounds were not found to differ greatly, teams that have access to more telemetry data could likely discern meaningful differences between tire compounds. The state-space framework's ability to assimilate new data in real time and output predictive uncertainty makes it a strong candidate for integration into race strategy tools.

Future work should extend the model across multiple races and drivers to better quantify compound-specific degradation patterns, refine priors using telemetry or surface-temperature data, and explore hierarchical structures for team- or track-level effects. Overall, the Bayesian state-space approach provides a statistically principled and computationally efficient foundation for studying tire behavior and optimizing strategy in Formula 1.

6 References

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