Statistical Learning: Project Presentation

G. Dunlavey, W. Ren, A. Taqi

Research Question

The competitive balance tax (implemented in 2002) is a rule implementing salary caps for baseball players in a given team. This paper attempts to uncover if there is any underlying difference in the rates and numbers of lost potential players (called "couldabeens") in the pre-rule era (1968-2002) and post-rule eras (2003-2018).

Methods: The Data

Our data comes from https://stathead.com/baseball/ and we mainly have four sets of data.

1. Rookie pitchers
2. Rookie position players
3. Retired pitchers
4. Retired position players

The research question in this paper hinges on classifying retired players of lost potential. To motivate this, we will first define our classifier for a "couldabeen".

Methods: The Couldabeen Classifier

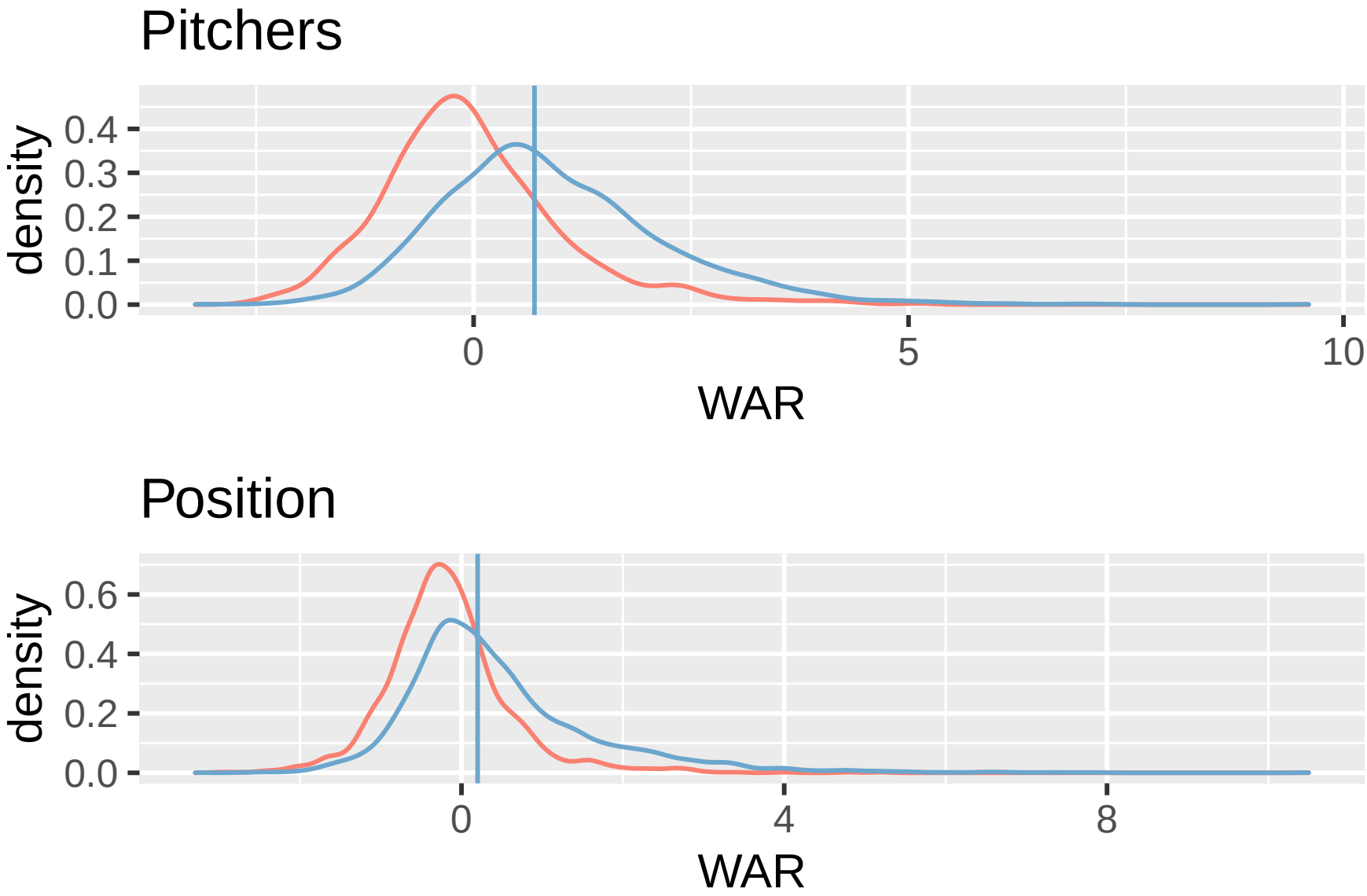
For a given year Y, we first compute the median rookie's WAR, call it m_Y. Additionally, compute the standard deviation of that data and call it σ_Y. Then, given a threshold $t \in \mathbb{R}$, we construct the corrosponding classifier for "couldabeen" status C of a given retired player p (from the year Y) to be as follows:

$$C(p) = \begin{cases} \textit{True}, \text{WAR}_p \geq m_Y + t\sigma_Y \\ \textit{False}, \text{WAR}_p < m_Y + t\sigma_Y \end{cases}$$

Visualization: Couldabeen Classification

- We can visualize the densities of the WAR statistic for each type of player to visualize our research question.
- In blue, we have the rookie players (with the median line denoted), and in red, we have the corrosponding retired players.
- As such, we can visualize the "couldabeens" as the retired players to the left of the median line (if the threshold $t = 0$), and we corrospondingly count the number of couldabeens based on year, from which we make our inference on the impact of Year.

Visualization: Couldabeen Classification

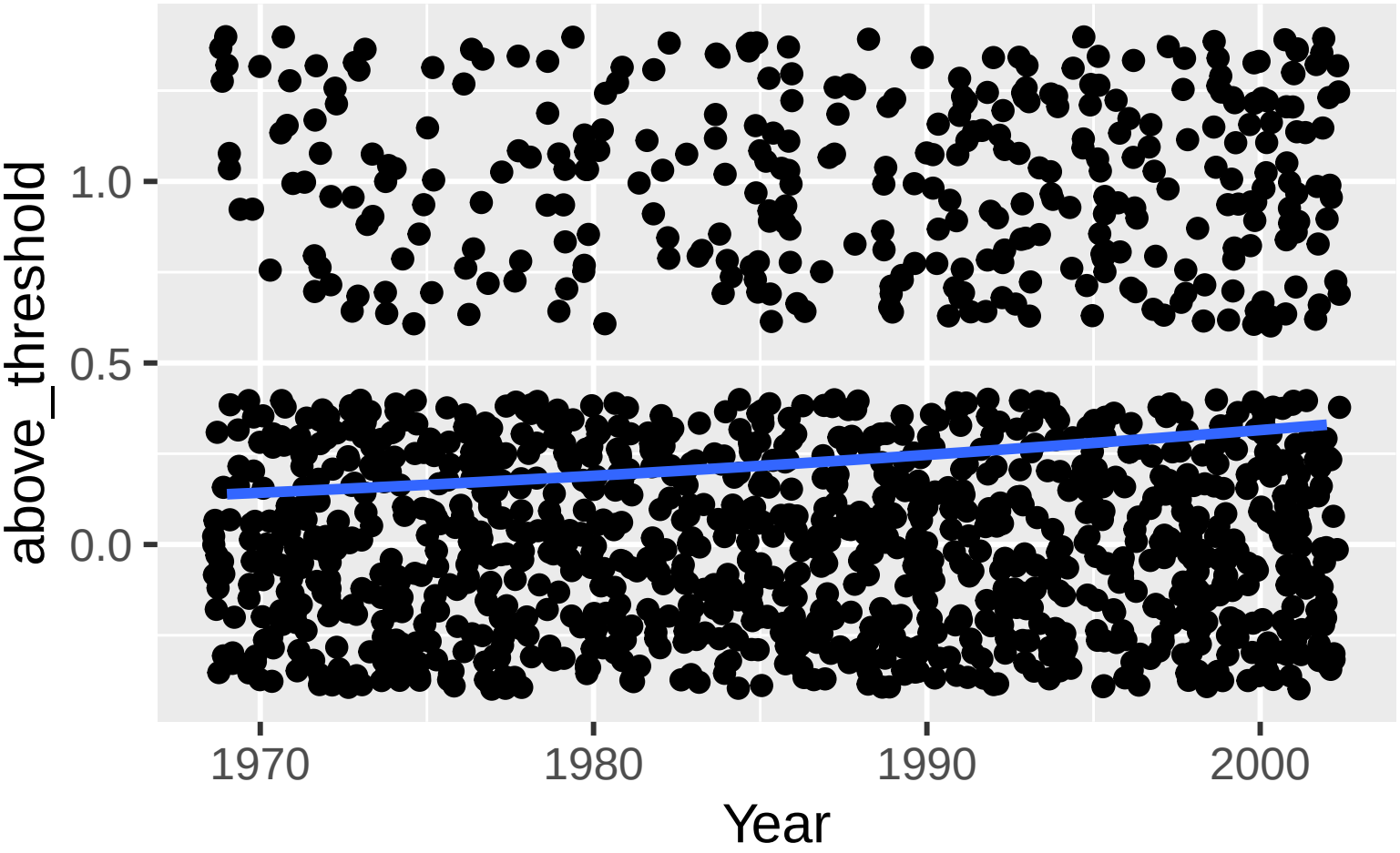


Methods: Modeling

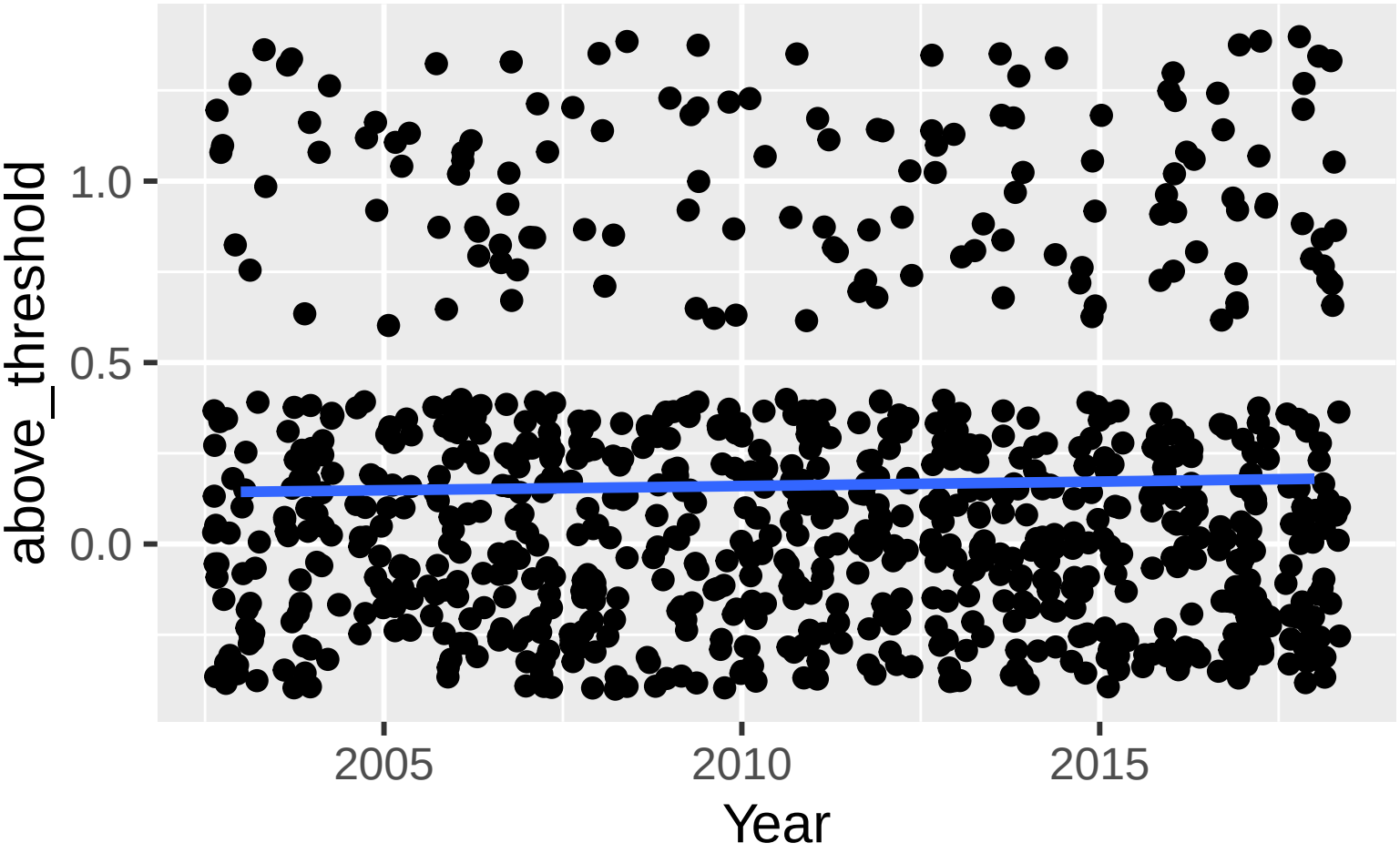
Once every retired player is classified appopriately, we run two primary models:

- **Logisitic Model**: On the retired players dataset, each player has a new column, `exceeds_threshold` which is the result of the classifier $C(p)$.
  - This classifier is a boolean, so we run two models on the pre-rule era and the post-rule era and see the effects `Year` has on `exceeds_threshold`.
  - Because there will always be "couldabeens", we do not expect a large effect size and hence a very significant result, however, the **sign** of our coefficient will be essential for our inference.
  - If our research hypothesis is correct (that there is an effect), we expect to see a positive coefficient for β_{Year}.

Logistic Model: Couldabeens Retirees (Pre-rule Era: 1969-2002)



Logistic Model: Couldabeens Retirees (Post-rule Era: 2003-2018)



Overall Results: Logisitic Models

Post-rule era

- Post-rule era model, we obtain a parameter $\beta_{Year} = 0.01781$. So indeed, $\beta_{Year} > 0$.

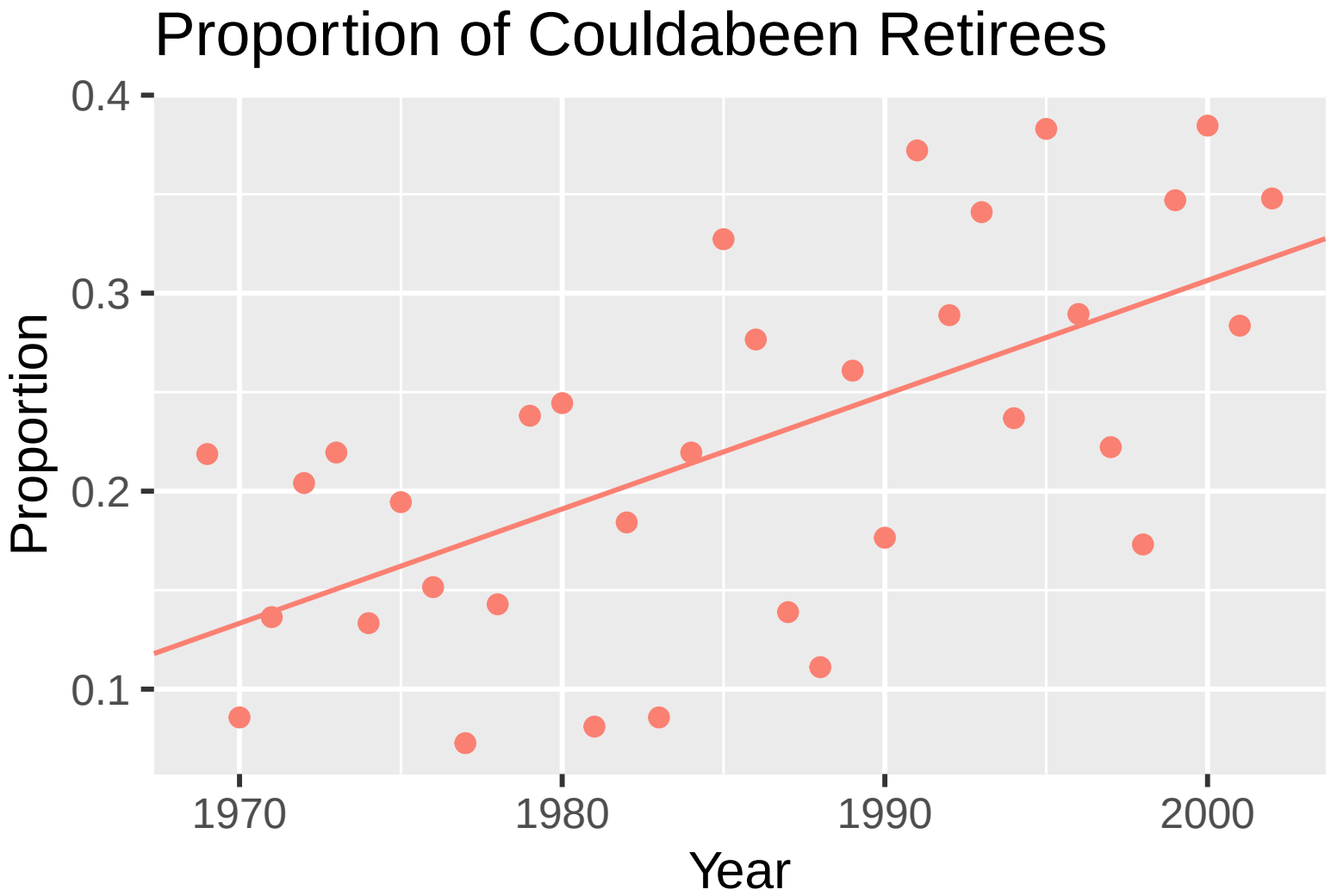
Pre-rule era

- For the pre-rule era model, we find $\beta_{Year} = 0.03392$. So indeed, we also have $\beta_{Year} > 0$. So, the effect is positive in both eras (will be discussed later in linear models).
- All in all, we may interpret the positive coefficient in both eras as saying that the probability a couldabeen is classified is greater at the end of an era than at its start for **both eras**.
- Conclude that up until the rule has been implemented, the proportion of couldabeens has been rising, and it rapidly drops in 2003 (year of the rule) only to increase again.

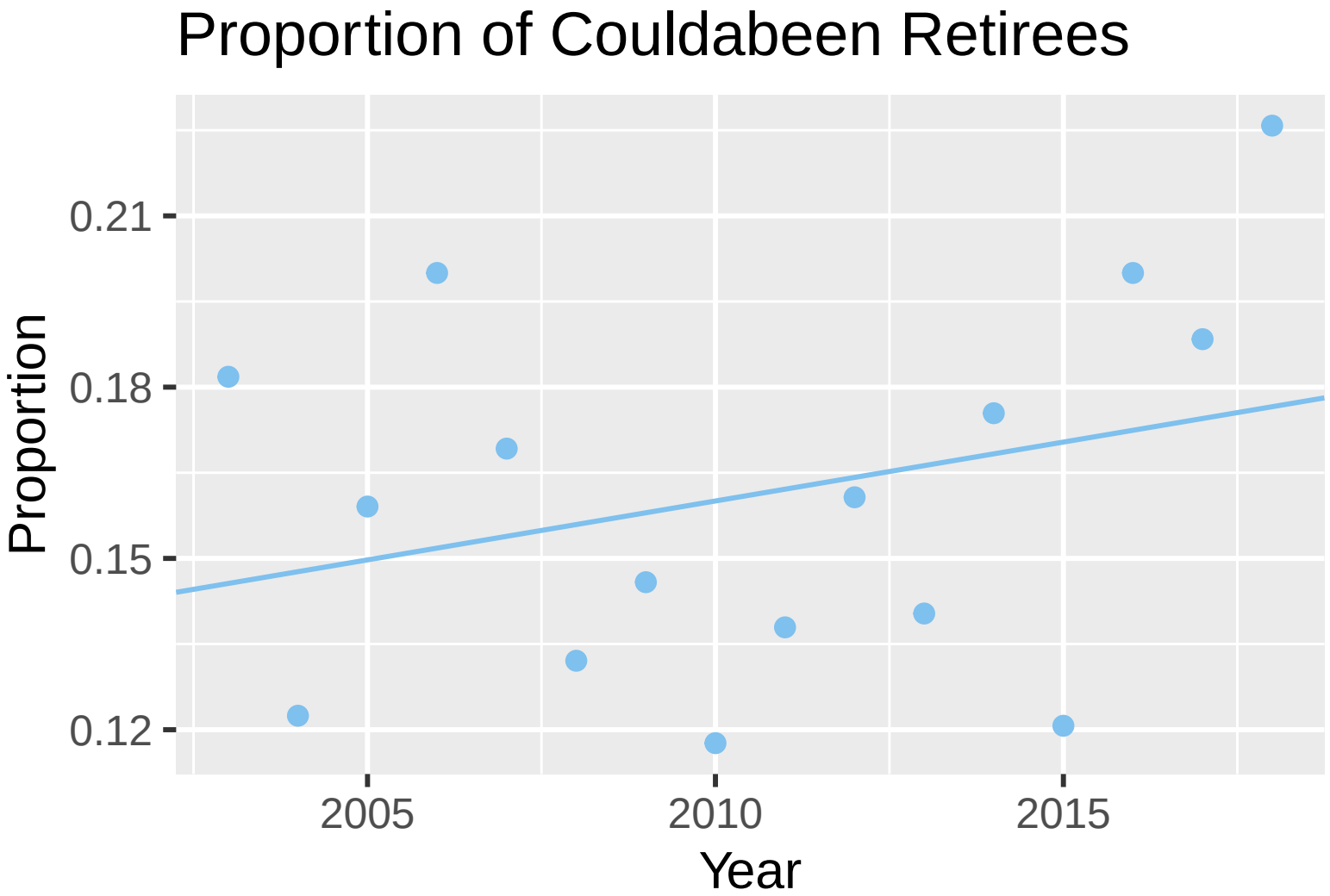
Methods: Modeling

- **Linear Model:** After aggregating all the retired players and their classifications, we summarize the data by year to obtain the proportion of retired players that were couldabeens that year, called `prop`.
  - As such, we now have 50 data points (for each year), and a response variable being the proportion of couldabeens.
  - So, we run a linear model fitting `Year ~ prop` for the pre-rule era and the post-rule era.
  - Again, because there will always be "couldabeens", we do not expect a large effect size and hence a very significant result.
  - Like the logistic models, the **sign** of our coefficient will be essential for our inference.
  - If our research hypothesis is correct (that there is an effect), we expect to see a positive coefficient for β_{Year}.

Linear Model: Couldabeens Retirees (Pre-rule Era: 1969-2002)



Linear Model: Couldabeens Retirees (Post-rule Era: 2003-2018)



Overall Results: Linear Models

Post-rule era

- Post-rule era model: $\beta_{Year} = 0.002064$. As such, since $\beta_{Year} > 0$.
- There is evidence that the rule has lead to an increase in the proportion of couldabeens.
- Predictions: Initially, the post-rule model predicts that in 2003 we get a proportion of $\beta_0 + 2003\beta_1 = 0.144$ and in 2018, we get a proportion of $\beta_0 + 2018\beta_1 = 0.177$.

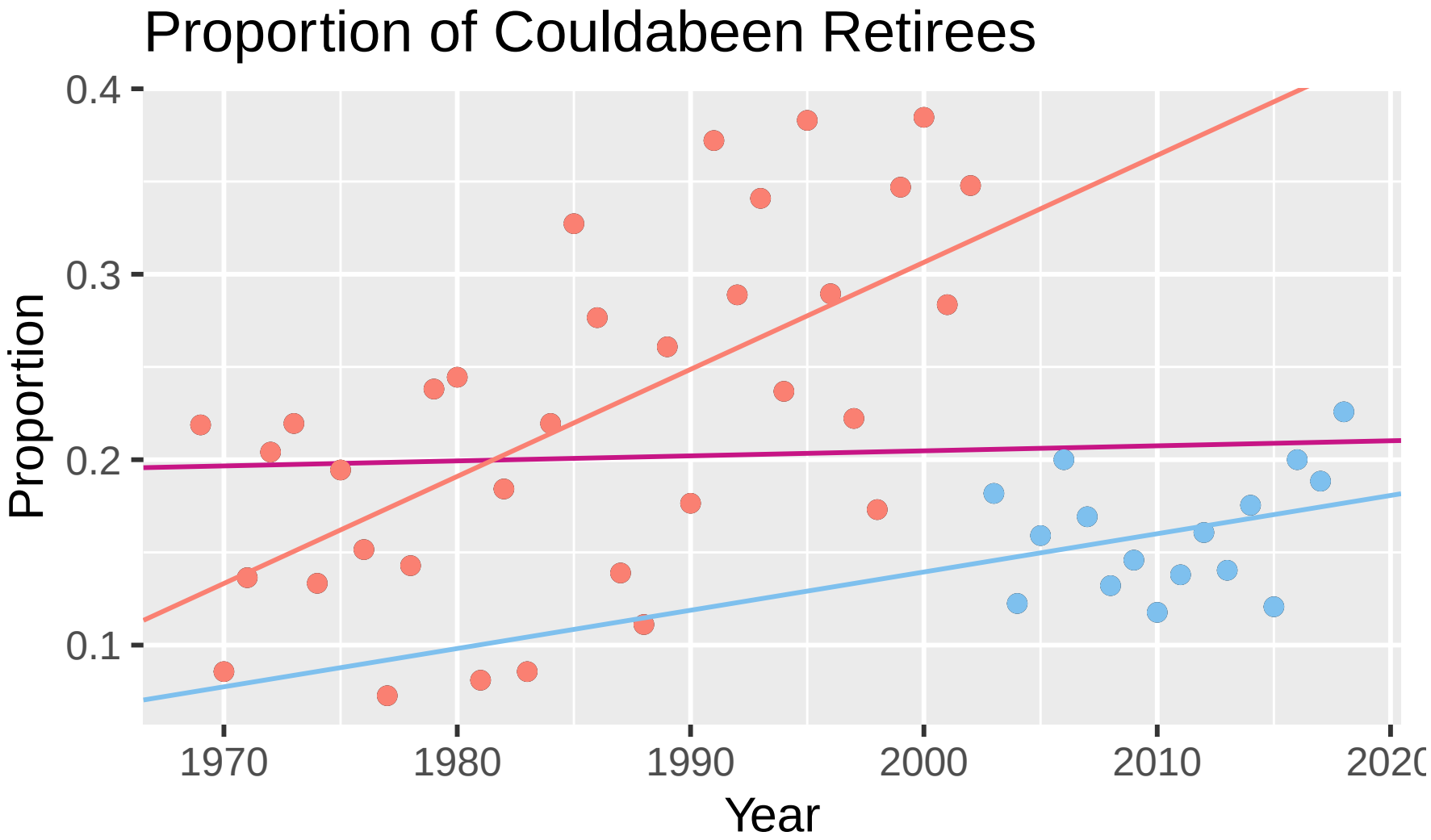
Pre-rule era

- Pre-rule era, we obtained a parameter $\beta_{Year} = 0.005773$. As such, we also have $\beta_{Year} > 0$.
- Conclude that up until the rule has been implemented, the proportion of couldabeens has been rising, and it rapidly drops in 2003 (year of the rule) only to increase again.

Simpson's Paradox

- We chose to partition the dataset into the post-rule and pre-rule eras and fit a linear model `Year ~ prop`.
- In both partitions, we find that the parameter $\beta_{Year} > 0$.
- However, if we do not make the partition, we find that $\beta_{Year} \approx 0$.
- This raises some questions regarding the role our partition plays in our inference and modeling choices.
- In fact, this is *Simpson's Paradox*.

Simpson's Paradox



Threshold Stability

Now, we will analyze the effects of the threshold t on the impact of our β_{Year} variable in our linear models. It is important to see what the effects are since our inference relies on β_{Year} being positive for any $t \in \mathbb{R}$. Recall the definition of the Couldabeen classifier:

The Couldabeen Classifier

Given a threshold $t \in \mathbb{R}$, we construct the corrosponding classifier for "couldabeen" status C of a given retired player p (from the year Y) to be as follows:

$$C(p) = \begin{cases} \textit{True}, \text{WAR}_p \geq m_Y + t\sigma_Y \\ \textit{False}, \text{WAR}_p < m_Y + t\sigma_Y \end{cases}$$

Threshold Stability

- Otained a positive result on the slope of β_{Year} for a particular threshold in the post-rule era.
- Varying the threshold tells another story.
- Run a linear model with `Year ~ prop` against a varying threshold t.
- Then, we found that β_{Year} is quite unstable.
- We obtained the following graph on the next slide.

Threshold Stability

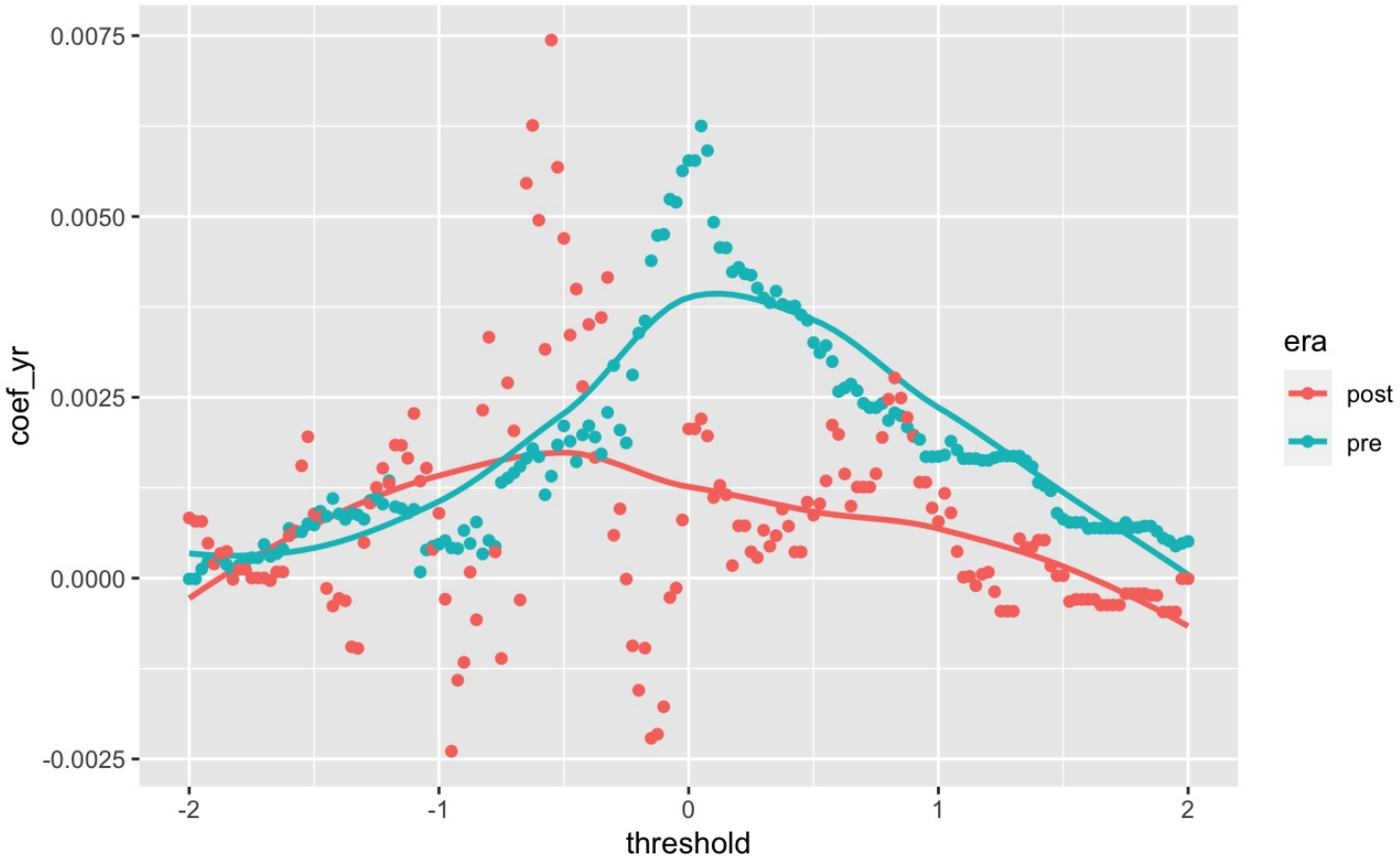


Figure 1: Parameters of the Linear Model against varying threshold for couldabeen status

Threshold Stability: Possible Adjustments

- Thresholds every year were calculated as a function of *only* that year's data.
- So, the sample from which we obtain the threshold by each level (corrosponding to each year) is very small meaning small changes to the threshold cause high levels of noise in our final model.
- To treat this problem, we may consider "smoothing" the threshold out by taking the data of that year and adjacent years. For instance, instead of considering just 2018 data, we may take 2017-2019 data for a "window length of 1".
- Furthermore, the addition of some supplementary yearly salary/budgets data may be useful as another predictor since `Year` alone does not seem to have good explanatory power.

References

1. https://stathead.com/baseball/