My title*

My subtitle if needed

First author Another author

February 12, 2024

First sentence. Second sentence. Third sentence. Fourth sentence.

1 Introduction

The COVID-19 pandemic has profoundly disrupted education systems worldwide, compelling schools and districts across the United States to rapidly adapt their learning models. In 2020 and 2021, educational institutions faced unprecedented challenges, transitioning between in-person, hybrid, and virtual learning models in response to evolving public health guidelines and infection rates. This shift has brought into sharp focus the need to understand the implications of these various schooling models on educational outcomes.

This paper delves into a comprehensive analysis across 11 U.S. states, examining the relationship between different schooling models and their impact on student enrollment and staffing patterns. The unique dataset compiled for this study encompasses a variety of metrics, including total enrollment, in-person and virtual attendance, as well as staff count across different learning models. By analyzing data from kindergarten to 12th grade, this study provides a granular view of how the pandemic has reshaped the educational landscape across these states.

Our findings reveal significant variations in how states have navigated the challenges posed by the pandemic, with notable differences in the adoption of in-person, hybrid, and virtual learning models. We observe that these variations are not only reflective of public health policies but also indicate broader socio-economic and demographic influences. For instance, preliminary analysis suggests that shifts to virtual learning correlate with changes in student enrollment, raising questions about equity and access in education during these challenging times.

*Code and data are available at: LINK.

The remainder of the paper is structured as follows: Section 2 provides a detailed overview of the data and methodology employed in this study. Section 3 presents an in-depth analysis of the schooling models across the 11 states, offering insights into the trends and patterns observed in the data. Section 4 discusses the key findings, exploring the implications of these schooling models on educational outcomes. Finally, Section 5 concludes with a reflection on the study's findings, limitations, and potential directions for future research in this critical area of educational policy.

The remainder of this paper is structured as follows. Section 2....

2 Data

2.1 Data Source and Collection

The data utilized in this study is obtained from the compilation of district-level schooling models and state standardized assessment data, originally featured in the paper "Pandemic Schooling Mode and Student Test Scores: Evidence from US School Districts" (Jack 2023) published in the American Economic Review: Insights in June 2023. (AEA 2022). The primary dataset encompasses schooling mode data from the 2020–2021 academic year across 11 U.S. states, integrating various educational approaches during the pandemic, including in-person, hybrid, and virtual learning environments. These datasets were sourced from COVID-19 School Data Hub (USA 2022), district-level state standardized assessment data from spring 2016–2019 and 2021, and additional data demographic statistics from the National Center for Education Statistics (NCES) to establish a comprehensive analytical framework.

Our analyses incorporate three categories of data: district-level schooling modes, state standardized assessment results from the academic years 2016–2019 and 2021, and auxiliary datasets that encompass district demographics and county-level variables. The following subsections detail the sources, collection methodologies, and data cleaning procedures undertaken to ensure the accuracy and reliability of the datasets for our analysis.

State Score Data: This dataset encompasses state-level academic performance statistics from 2016 to 2020. Variables include the proportion of in-person, virtual, and hybrid learning, participation rates, standardized test pass rates, COVID-19 case rates per 100,000 in school zip codes, peak monthly cases, total enrollment figures, and political voting shares by district.

Learning Model Data: This dataset details the learning models adopted by school districts in Colorado, Connecticut, Ohio, Virginia, West Virginia, Wyoming, Mississippi, Rhode Island, Minnesota, Massachusetts, and Wisconsin. Each state's data outlines the specific learning model (in-person, virtual, hybrid) employed over time, enrollment figures, and staffing counts.

2.2 Data Cleaning and Processing

We used R (R Core Team 2022) for data cleaning and processing, utilizing packages like tidyverse (Wickham et al. 2019) for data manipulation and janitor (Firke 2023) for cleaning column names. The cleaning process involved standardizing learning model categories, selecting columns of interest, and simplifying data for analysis. We integrated data from different states, and made sure that variations in reporting and measurement were addressed while combining them into one. For instance, some states categorized their schooling mode as "In-person," while others used "In-Person." To ensure they are equivalent, we standardized these terms. We also conducted a check for missing data values, and imputed or excluded them as appropriate based on the context. The variables were also renamed for clarity and consistency across different states' datasets. A sample of cleaned state score data can be seen in (**tbl__cleaned__data?**).

Table 1: Sample of Cleaned State Score Data

State	Year	Share In-person	Share Virtual	Share Hybrid	Participation	Pass Rate	Covid cases rate per 100k	Total Enrollment
CO	2016	0.8586572	0.0600707	0.0812721	86.28333	0.3296667	29.04677	1132
CO	2016	0.9399293	0.0600707	0.0000000	91.75000	0.2460000	31.04686	8723
CO	2016	0.0000000	0.2756184	0.7243816	95.86667	0.2526667	31.53898	18657
CO	2016	0.0000000	0.5759717	0.4240283	98.58334	0.0950000	31.54341	5725
CO	2016	0.2155477	0.0600707	0.7243816	96.35000	0.3298333	29.81067	1001
CO	2016	0.2155477	0.4664311	0.3180212	97.26667	0.3730000	31.54496	35817

```
`geom_smooth()` using formula = 'y ~ x'
`geom_smooth()` using formula = 'y ~ x'
```

Talk more about it., SURE

And also planes (**?@fig-planes**). (You can change the height and width, but don't worry about doing that until you have finished every other aspect of the paper - Quarto will try to make it look nice and the defaults usually work well once you have enough text.)

Talk way more about it.

3 Model

The goal of our modelling strategy is twofold. Firstly,…

Here we briefly describe the Bayesian analysis model used to investigate… Background details and diagnostics are included in Appendix B.

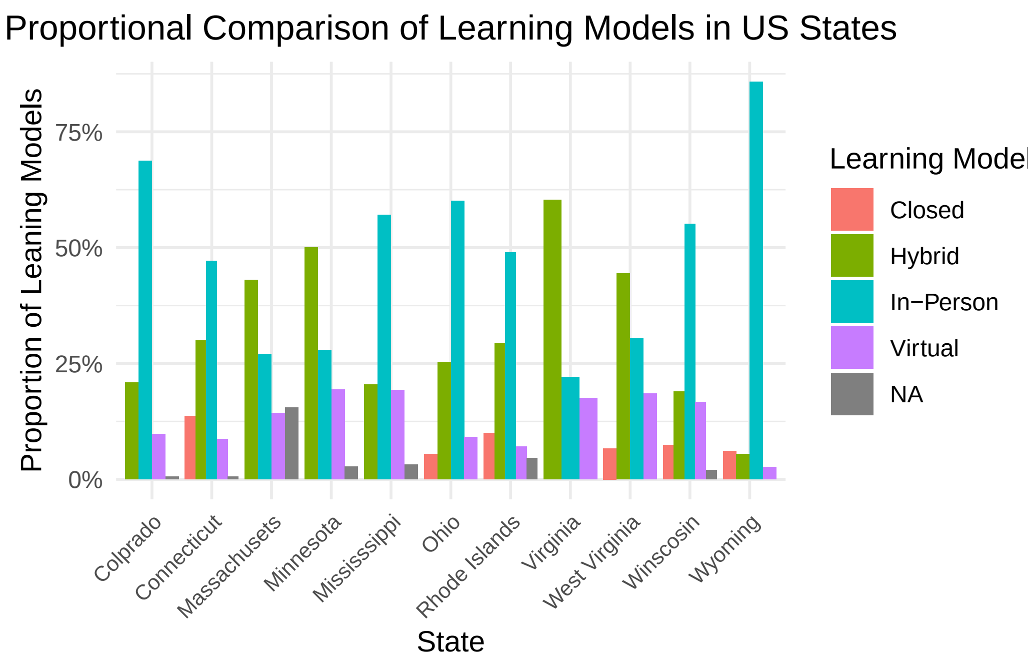

Figure 1: Bills of penguins

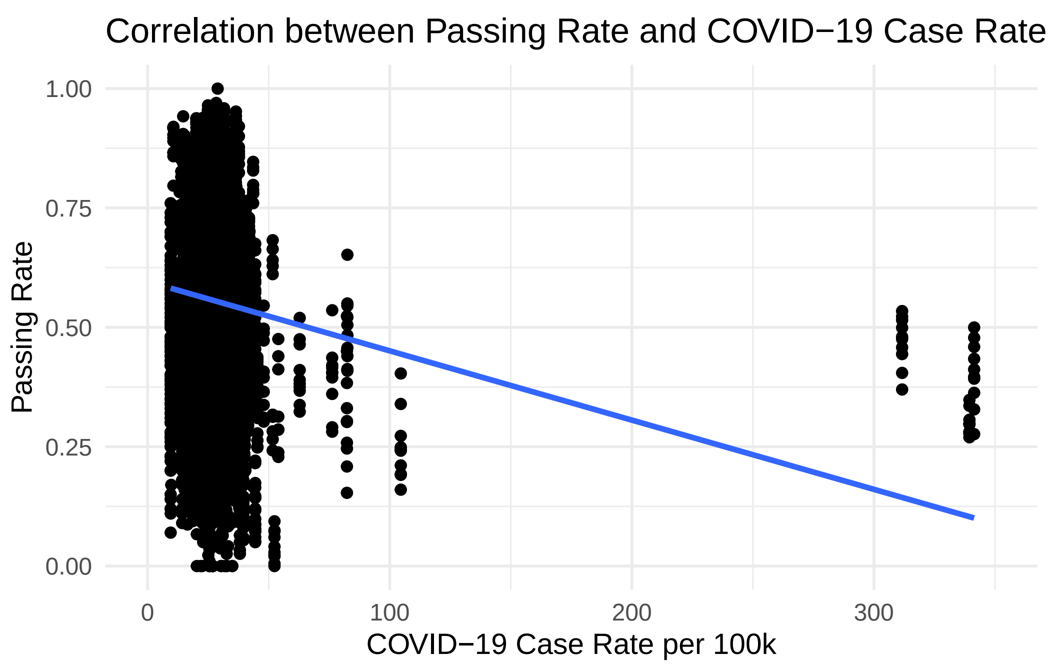

Figure 2: Bills of penguins

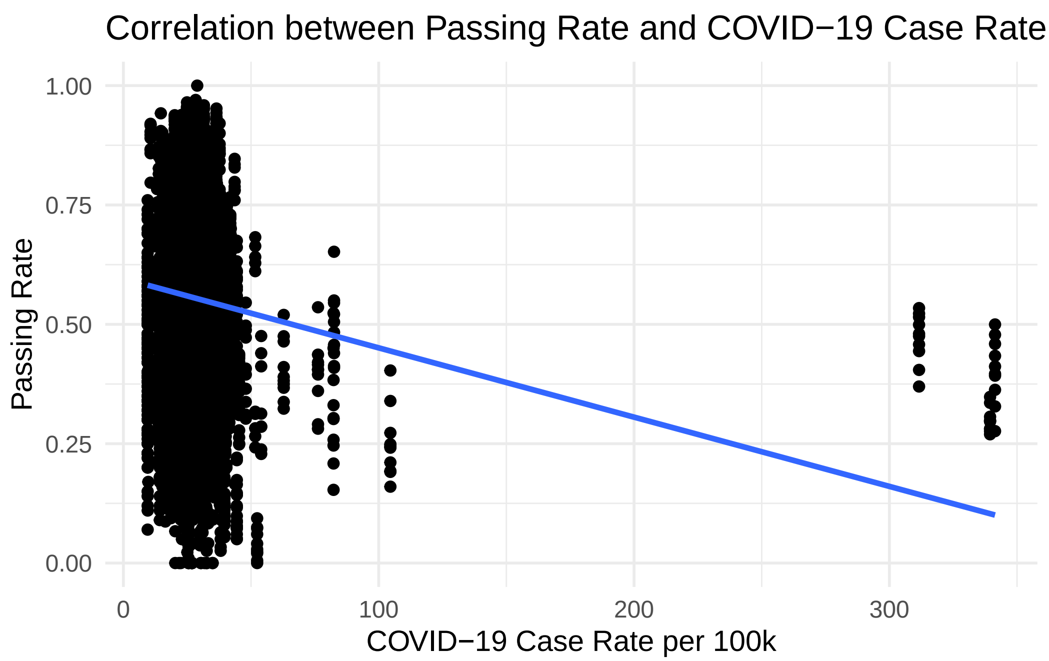

Figure 3: Bills of penguins

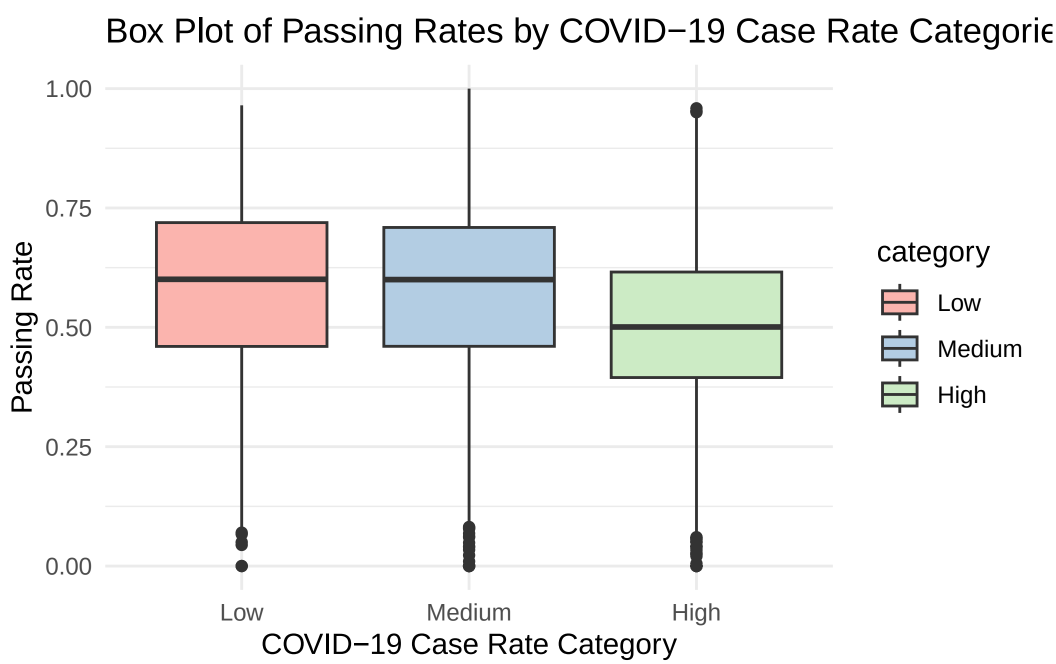

Figure 4: Bills of penguins

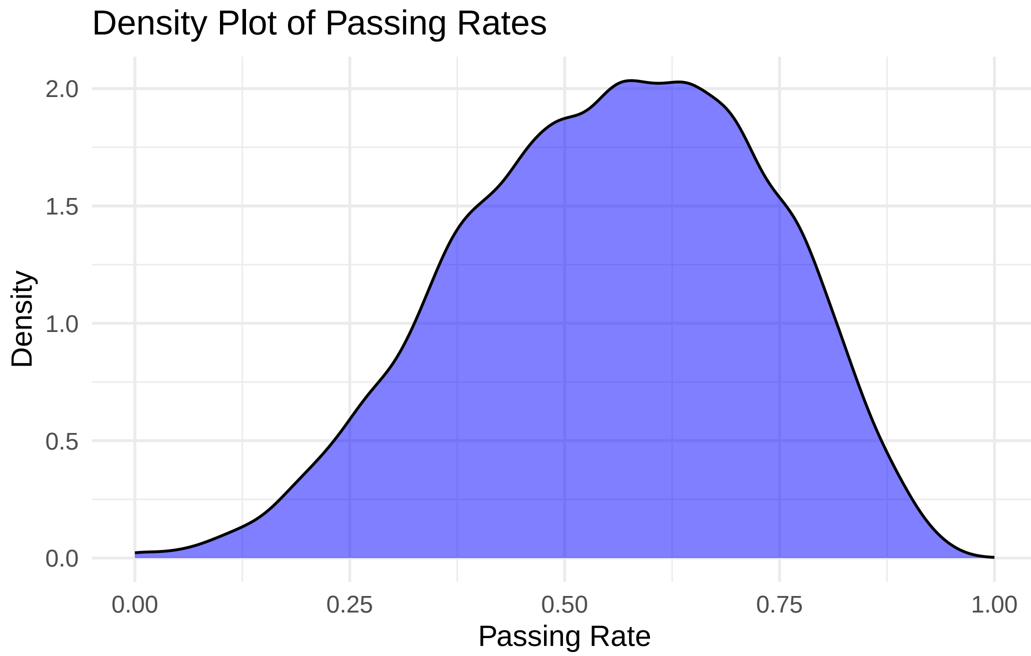

Figure 5: Bills of penguins

State	Avg. Share In-person	Avg. Share Virtual	Avg. Share Hybrid	Avg. Participation	Avg. Pass Rate
CO	65.68918	10.285258	24.02556	95.11431	36.03400
CT	55.21059	6.625613	31.45075	98.68581	59.33747
MA	33.46283	9.333824	57.20335	100.00000	53.69718
MN	35.23909	8.302583	56.45833	96.34993	56.35686
MS	56.80734	17.653758	25.53891	100.00000	72.84675
OH	63.31093	9.349329	26.61283	99.66106	69.27725
RI	54.77593	5.261545	34.39462	98.90301	41.80093
VA	16.28958	27.904606	55.80582	99.35298	76.24432
WI	68.34940	5.536344	17.69383	99.04141	44.81849
WV	31.84275	16.216216	48.20639	94.10710	40.05973
WY	85.46875	2.395833	5.62500	99.68056	55.27684

Figure 6: Relationship between wing length and width

State	Avg. Share In-person	Avg. Share Virtual	Avg. Share Hybrid	Avg. Participation	Avg. Pass Rate
CO	63.66436	10.832368	25.50328	81.01494	32.31432
CT	55.20204	6.625613	31.45931	93.31494	50.27606
MA	33.46283	9.333824	57.20335	95.58099	43.86268
MN	35.40717	8.277188	56.31564	87.20716	46.03220
MS	57.07332	17.624205	25.30248	97.04833	60.17785
OH	63.30790	9.319841	26.64837	97.11603	58.88783
RI	54.77593	5.261545	34.39462	90.82130	34.79347
VA	16.28958	27.904606	55.80582	84.78617	54.15240
WI	68.34940	5.536344	17.69383	95.60902	38.69319
WV	31.84275	16.216216	48.20639	87.97907	32.07227
WY	85.46875	2.395833	5.62500	97.16042	51.90012

Figure 7: Relationship between wing length and width

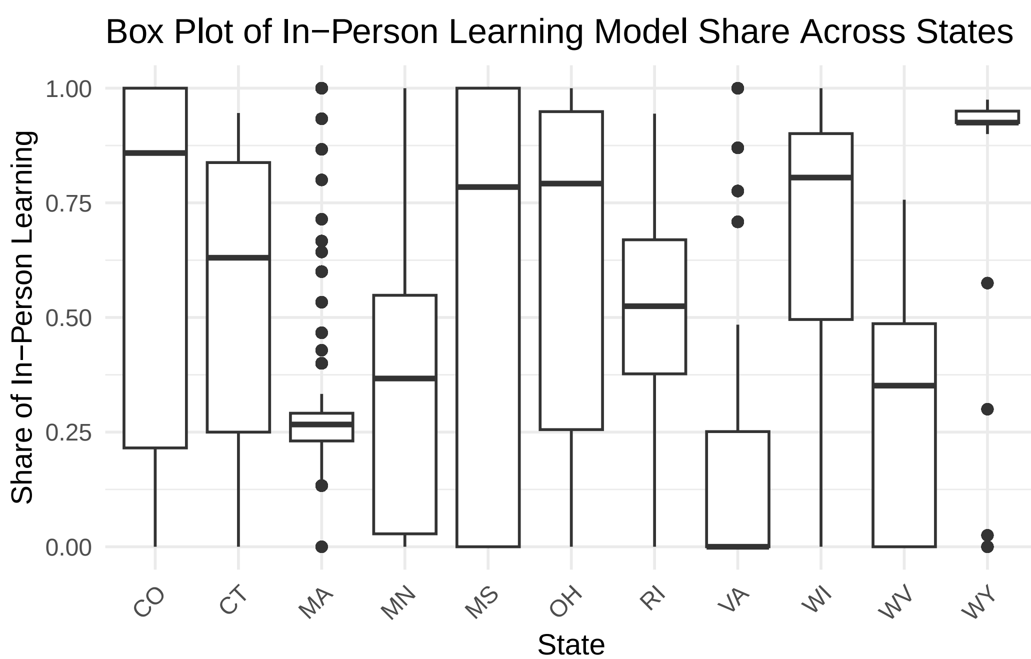

Figure 8: Relationship between wing length and width

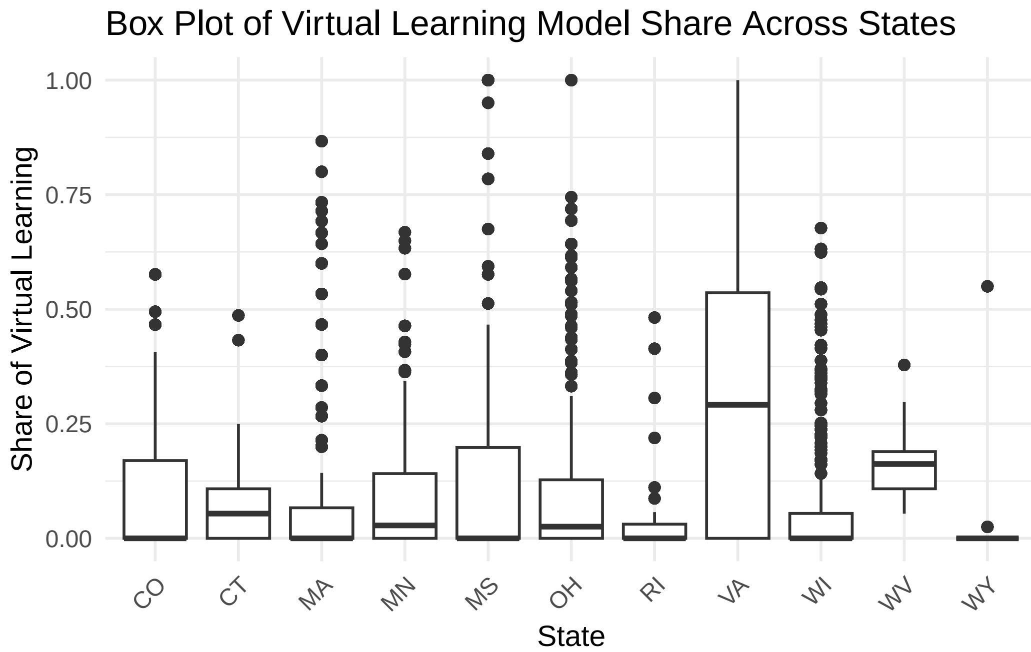

Figure 9: Relationship between wing length and width

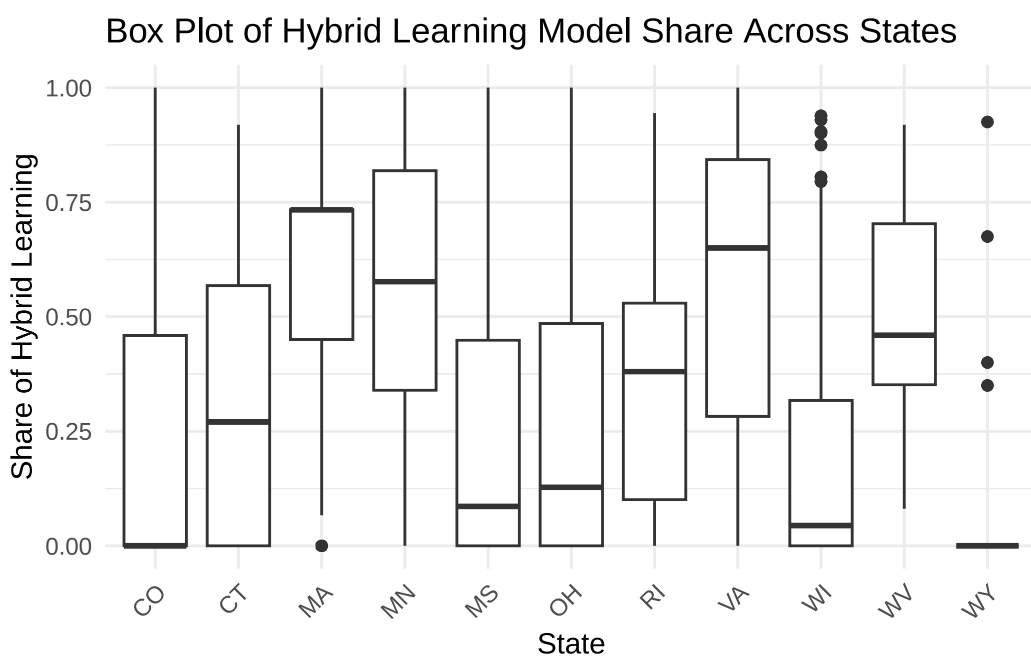

Figure 10: Relationship between wing length and width

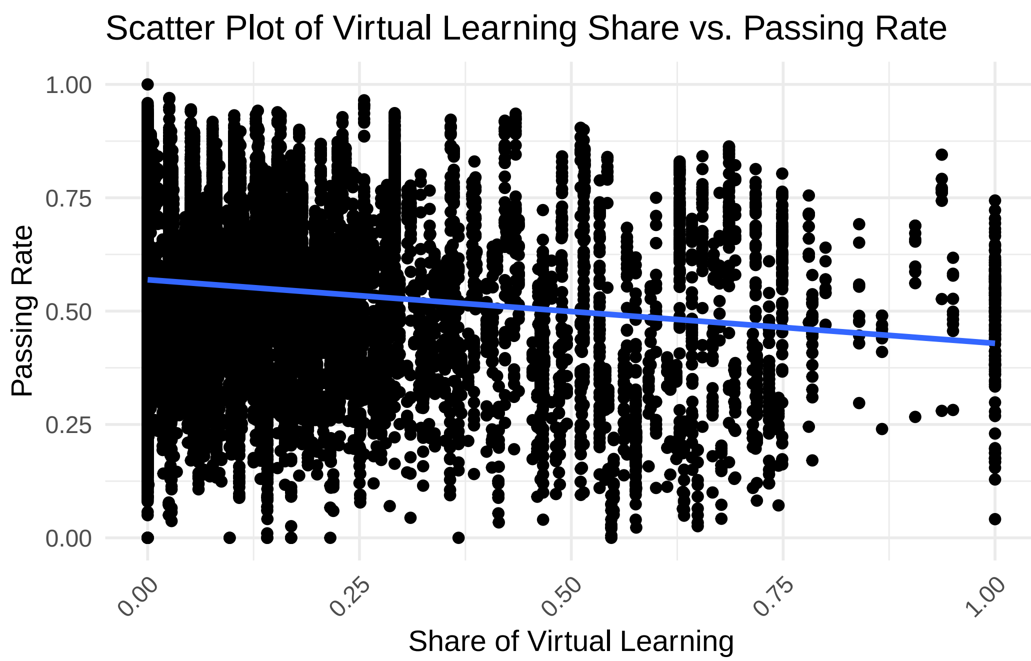

Figure 11: Relationship between wing length and width

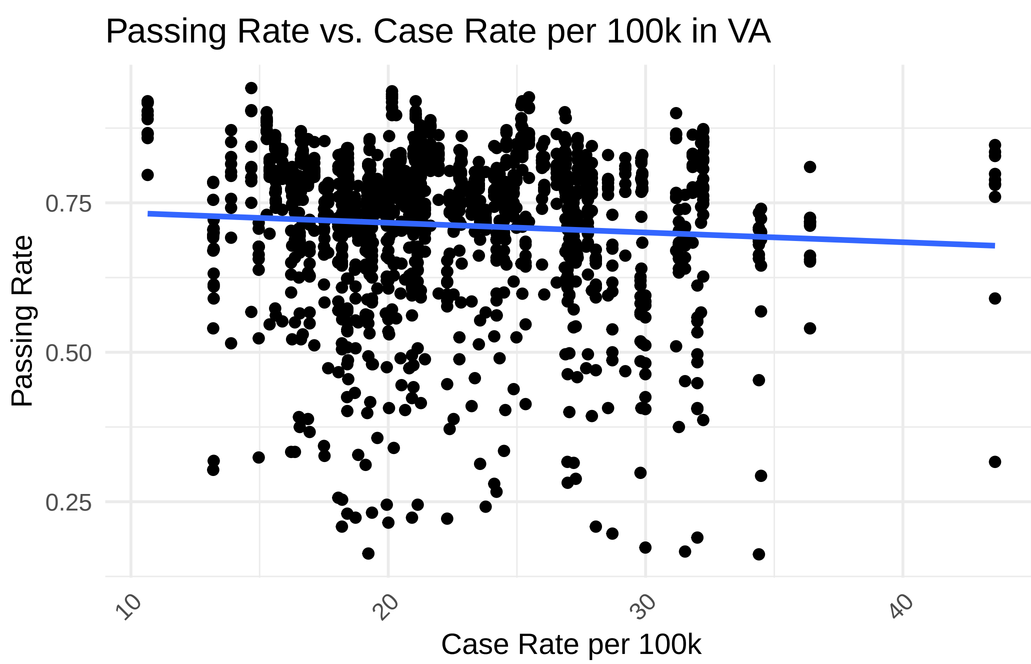

Figure 12: Relationship between wing length and width

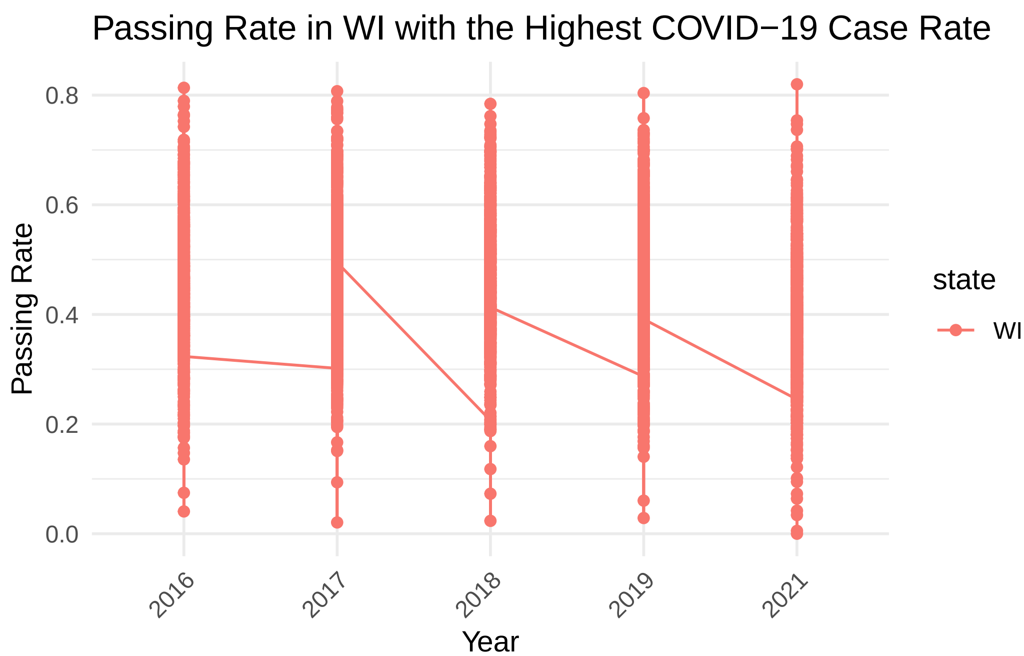

Figure 13: Relationship between wing length and width

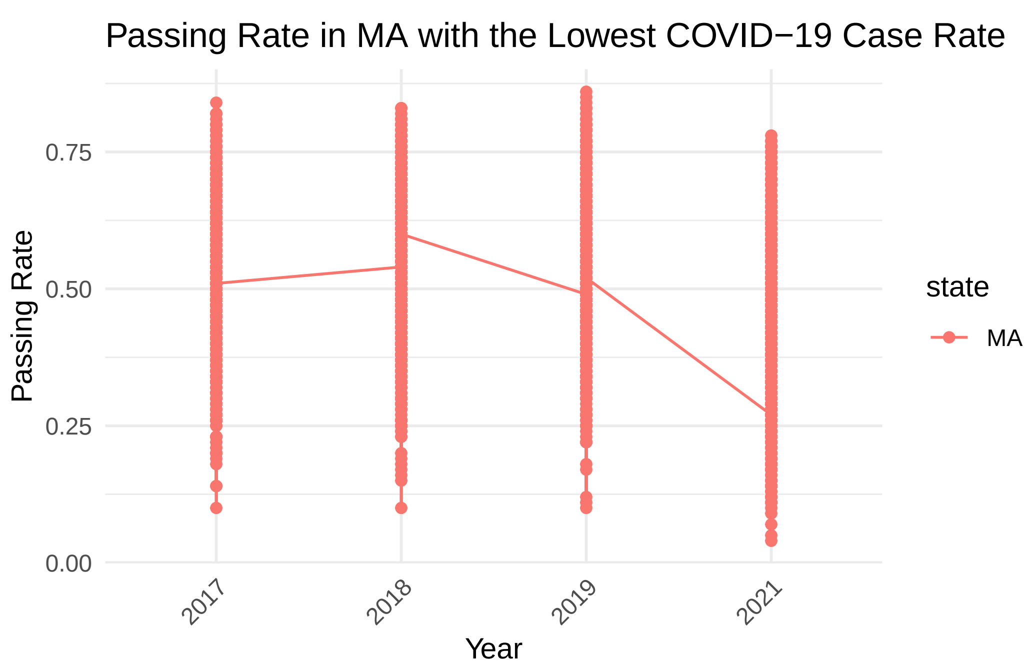

Figure 14: Relationship between wing length and width

3.1 Model set-up

Define y_i as the number of seconds that the plane remained aloft. Then β_i is the wing width and γ_i is the wing length, both measured in millimeters.

$$
\begin{aligned}
y_i|\mu_i, \sigma &\sim \text{Normal}(\mu_i, \sigma) && (1)\\
\mu_i &= \alpha + \beta_i + \gamma_i && (2)\\
\alpha &\sim \text{Normal}(0, 2.5) && (3)\\
\beta &\sim \text{Normal}(0, 2.5) && (4)\\
\gamma &\sim \text{Normal}(0, 2.5) && (5)\\
\sigma &\sim \text{Exponential}(1) && (6)
\end{aligned}
$$

We run the model in R (R Core Team 2022) using the `rstanarm` package of Goodrich et al. (2022). We use the default priors from `rstanarm`.

3.1.1 Model justification

We expect a positive relationship between the size of the wings and time spent aloft. In particular…

We can use maths by including latex between dollar signs, instance θ.

4 Results

Our results are summarized in **?@tbl-modelresults**.

5 Discussion

5.1 First discussion point

If my paper were 10 pages, then should be be at least 2.5 pages. The discussion is a chance to show off what you know and what you learnt from all this.

5.2 Second discussion point

5.3 Third discussion point

5.4 Weaknesses and next steps

Weaknesses and next steps should also be included.

Appendix

A Additional data details

B Model details

B.1 Posterior predictive check

In **?@fig-ppcheckandposteriorvsprior-1** we implement a posterior predictive check. This shows...

In **?@fig-ppcheckandposteriorvsprior-2** we compare the posterior with the prior. This shows...

References

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