ASSESSING THE EFFECTIVENESS OF STATE-LEVEL POLICY INTERVENTIONS ON DOMESTIC AIR TRAVEL DURING THE COVID-19 PANDEMIC

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ABSTRACT

In our increasingly interconnected world, the potential for infectious diseases to spread quickly and globally is of substantial epidemiological concern. Travel restrictions, herein defined as the 27 executive orders issued between March 2020 and October 2021 by state governments to restrict interstate travel, are a potential policy solution to control the spread of disease. The social, economic, and health-related consequences of travel restrictions have been previously explored in the literature. However, the effectiveness of travel restrictions in reducing the frequency of interstate air travel within the United States is less well understood. This study employs a holistic approach to compare the effectiveness of travel restrictions in decreasing commercial flight frequency between U.S. states during the recent coronavirus pandemic. Using Regression Discontinuity Design (RDD) and time series analysis techniques, it considers how changes in the number of arriving flights within a state have been affected by the recent implementation of a travel restriction. The results suggest that these restrictions are dramatically less effective than policymakers have likely intended. Even after controlling for national trends, there is not strong evidence to support the hypothesis that the implementation of a travel restriction will lead to a significant decrease in the frequency of commercial air travel between states. These findings suggest further that the causal effects of travel restrictions on COVID-19 case counts are insignificant and raises questions concerning the costs and benefits of implementing ineffective travel restrictions when the resulting economic and social consequences are undesirable.

INTRODUCTION

The impact of COVID-19 on the aviation/travel industry

On January 31, 2020, the World Health Organization (WHO) declared the outbreak of SARS-CoV-2 a Public Health Emergency of International Concern. Since then, the pandemic has transformed daily life in innumerable ways. In addition to waves of sudden and unprecedented economic disruptions, the United States has reported over 693,000 deaths and 43.2 million cases as a result of the COVID-19 virus (WHO, 2021). In response, measures have been taken at the local, federal, and international level to help curb the social and economic effects of the pandemic while lessening the severity of the outbreak for all Americans. Beginning with the creation of the White House Coronavirus Task Force on January 27 and the declaration of a public health emergency on January 31, the federal government began to put in motion pre-established executive, legal, and regulatory pandemic response procedures (Wallach and Meyers, 2020).

The first global air travel restriction was implemented on February 2, 2020, when those en route to the United States from the Hubei province of China faced a 2-week home based quarantine. On March 19, California become the first state to issue a stay-at-home order (Exec. Order No. 33-20). While the federal government has sole authority over international borders, it defers to states when it comes to the implementation of quarantines during public health emergencies and did so when it came to the enforcement of stay-at-home orders and travel restrictions as well.

Despite giving states the broad authority to do what it necessary to protect their people's general health and welfare, the U.S. Supreme Court has long recognized an implicit constitutional right to travel, consisting of three elements: the right to enter and leave a state, the right “to be treated as welcome visitor rather than an unfriendly alien” when visiting a state, and the right to become a citizen of any state. These elements are grounded in the commerce clause and the privileges and immunities clause of Article IV (526 U.S. 489). While the commerce clause prevents discrimination against other states’ commerce, the privileges and immunities clause inhibits discrimination against other states’ citizens (Canaparo, 2020). As result of these laws, broad federal restrictions on domestic travel were never implemented, and action at the statewide level taken to “flatten” the curve of disease transmission has varied significantly. To date, twenty-seven U.S. states have enacted at least one restriction on interstate travelers through executive orders issued by governors or state agencies (Brown and Marples, 2021). Figure 1 visualizes the variance in lengths and dates of said restrictions between states.

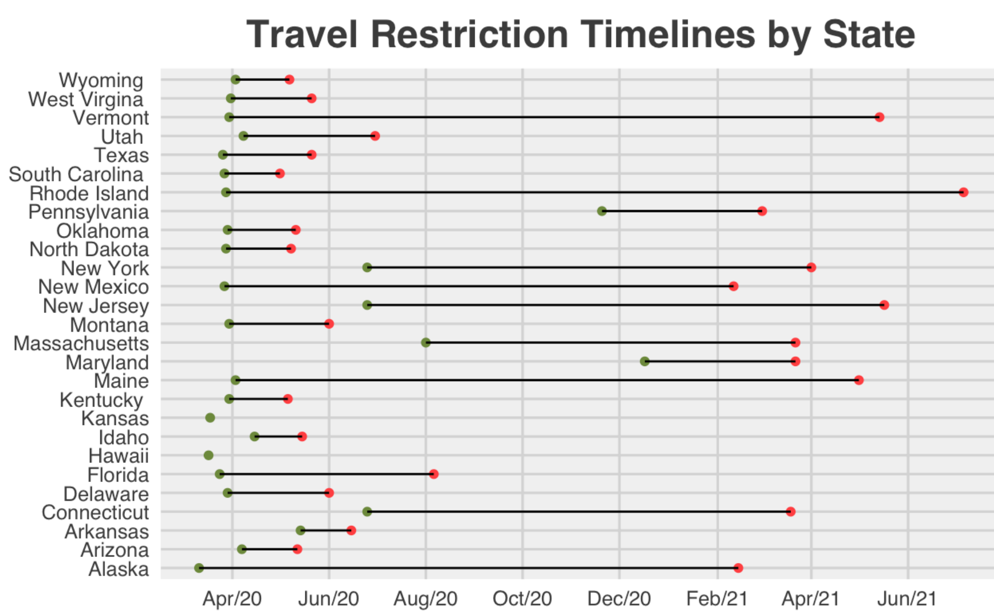


Figure 1: Timeline of the 27 travel restrictions issued in the form of an executive order, with a green point signaling the start of the restriction and a red point signaling its end. As of October 2021, Hawaii and Kansas have not officially rescinded their restrictions.

As a matter of public health policy, the potential effectiveness of travel restrictions for the spread of disease must be considered relative to their economic consequences. Although the effects of the coronavirus pandemic are unprecedented, this is not the first time the commercial airline industry has had to bounce back after a crisis. Events such as the 2008 Great Recession, 9/11/2001 attacks, and the SARS and Zika virus epidemic led to a notable drop in air travel. (Suau-Sanchez et al., 2020). While previous disease outbreaks have had significant impacts on interstate travel, 2020 was the first time that both domestic and international travel had been restricted in such a way (Suau-Sanchez et al., 2020). These restrictions, paired with other precautions, have led to a major decline in demand for leisure and business travel. Consequentially, there has been a decrease in the number of people traveling domestically within the United States and a shift in the ways in which they do so.

Considering the integral role that civil air transportation plays in economies around the world, it is in the best interest of the U.S. government to promote a prompt and full recovery. As reported by the Federal Aviation Administration (2020), all aviation activity, across both direct and catalytic sectors, amounts to more than 5 percent of the U.S. Gross Domestic Product, contributes $1.8 trillion in total economic activity, and supports nearly 11 million jobs. Worldwide, the airline industry has faced a dramatic revenue loss. Airlines reported a net loss of $5.2 billion in the first quarter of 2020, while domestic departures declined 71.5% in May 2020 as compared to the previous year (Hotle and Mumbower, 2021).

In response to these losses, the U.S. government intervened, and the Coronavirus Aid, Relief, and Economic Security (CARES) Act was signed into law on March 27,2020, providing $50 billion in financial assistance to passenger carriers through a combination of loans, loan guarantees, and payroll support (U.S. Congress, 2020). This helped minimize the economic effects of the pandemic and provided a much-needed financial lifeline to the industry. All 10 of the largest U.S. passenger carriers, along with 340 smaller passenger carriers, signed agreements to receive financial support. This act put into place requirements for airlines to maintain operations to the same domestic cities serviced pre-pandemic. Hotle and Mumbower (2021) found that reductions in domestic air service were not uniform. Larger airports faced more decline in departure operations and markets served in comparison to non-primary airports, meaning that the CARES Act was one of many important contributors to the observed variance in route frequency supplied by airlines.

Travel as a pathway for the transmission of disease

According to Chung (2015), the aviation industry's rapid growth in recent years has paved the way for rapid proliferation and spreading of diseases through people movement. This is an epidemiological concern that requires careful consideration and analysis. The travel sector is known to be a crucial disease transmission pathway through the mobility of infected persons and onboard transmission of various diseases (Sun et al, 2020; Grout et al, 2017). It is therefore agreed that air travel may have played a notable role in the spread of the COVID-19 virus. Given this understanding, the aviation industry had to adopt health and safety protocols such as the disinfection of aircraft, temperature screenings, and increased distancing of passengers on planes. However, considering the size and significance of the industry, the effectiveness of these measures lacks significant support.

The epidemiology of infectious diseases associated with air travel is an important concern, yet, before the onset of the coronavirus pandemic, has scarcely been discussed in the literature (Grout et al., 2017). Further, evidence relating to the impact of travel bans in response to other emerging infectious disease threats is inconsistent (Bielecki et al., 2020). A handful of similar projects have investigated the following, important question: How does air transportation (and other modes) contribute to the spread of COVID-19? (Suk and Kim, 2021)

Several studies have looked at the effects of global aviation on the spread of epidemics, concentrating on their geographical spread while considering spatial effects, local infection dynamics and the dispersal of individuals (Hufnagel et al, 2004). Methods vary, with researchers using these factors to empirically prove that travel restrictions and control measures can be effective in minimizing the spread of infectious diseases (Hufnagel et al, 2004). Complex system analysis, as well as the implementation of supervised and unsupervised machine learning techniques to trade trends in infection dynamics and travel, have been employed to reach similar conclusions (Sun et al., 2020; Wang et al., 2020).

Other researchers have explored the impact of international and domestic travel restrictions on COVID-19 infections in Asia, the early epicenter of the pandemic. Using volume data for Japan's public transportation network, domestic travel restrictions were found to be effective at preventing the spread of disease (Murano et al., 2021). In China, a global epidemic and mobility model observed that, although domestic travel restrictions had the ability to slow the overall progression of the epidemic only, international restrictions significantly affected the trajectory of transmission (Chinazzi et al., 2020). Additionally, using a spatial Durbin model and regression discontinuity design model, Liu et al. (2021) found concrete evidence that the severe decrease in flights had a spontaneous impact on controlling the spread of COVID-19 in the European market. These results indicate that travel restrictions put into place by governments have influenced the rate of COVID-19 transmission and positive cases within those countries.

A study by Errett et al. (2020) reviewed more than 2,000 research articles and found just six that explored the use of international travel bans to control the spread of emerging infectious diseases. They looked at four infectious diseases that have emerged in recent years, including the Ebola virus, SARS (Severe Acute Respiratory Syndrome), MERS (Middle East Respiratory

Syndrome) and the Zika virus and found only a handful of modeling studies, with none that evaluated the impact of an actual ban after it was implemented. In an analysis of the effectiveness of travel-related measures during the early phases of the COVID-19 pandemic, Grepin et al. (2020) identified 26 studies that investigated international or domestic measures, finding with high confidence that the adoption of travel measures led to important changes in the early phases of the COVID-19 pandemic. This resulted in reductions in transmission between Wuhan, Mainland China as well as additional reductions in the number of cases exported internationally. The review found that most studies of international travel measures did not account for domestic travel restrictions, and notes that this may have likely led to biased estimates.

It is unclear if the lessons from other infectious disease outbreaks are relevant in the context of COVID-19. In addition, it is difficult to apply findings from other countries to that of the United States, as government policy interventions and the extent to which citizens abide to such mandates have differed widely. Given the widespread implementation of travel restrictions and the likely economic and social consequences resulting from them, a more complete understanding of the effectiveness of these policies is warranted. To the researcher's knowledge, there lacks a comprehensive research study that assess the effectiveness of interstate travel restrictions in reducing the amount of commercial air travel between U.S. states. This study is unique in that it compares and evaluates measures taken by the 27 states that issued travel restrictions in response to the COVID-19 crisis and seeks to explain how these restrictions have impacted the severity of the pandemic in the United States.

The goal of this paper is to assess and analyze the effectiveness of travel restrictions on domestic air travel in the United States. More specifically, this research asks two primary questions: (1) Has the executive implementation of a domestic travel ban had a statistically significant effect on the frequency of commercial air travel between states? (2) What are the potential implications of these findings, considering the policy's intention of reducing the spread of the novel coronavirus? As COVID-19 variants continue to develop and the risk of another worldwide pandemic looms, this study can assist in evaluating the effectiveness of measures taken by state and local governments and potentially help inform future policies and regulations.

METHODOLOGY AND DATA

Data

The primary dataset used in this analysis was constructed using publicly available daily airport departures data from the U.S Bureau of Transportation. This data did not include charter flights nor air cargo flights. Variables include the date, airline carrier, departure airport and destination airport of each flight. Between March 1, 2020 and July 31, 2021, the most recent month for which data is available, 7,228,895 total domestic flights were flown in the United States. Although Delaware issued travel restrictions, no commercial airlines offered service to the state between June 2015 and February 2021, and it was therefore excluded from this analysis (Quinn, 2021).

The unique relationship between supply and demand within the commercial aviation industry allows *flight frequency* to be used as a primary unit of analysis. Airfare is generally considered to be an elastic product, meaning that its demand is extremely sensitive, a concept reflected in the practices of ticket pricing within the industry. The elasticity of air travel was observed during the COVID-19 pandemic, which heavily impacted factors that typically influence an airline's economic performance, such as consumer income and the overall need for airline services. Considering the high fixed costs of operating an airplane, these shifts in demand ultimately resulted in significant movements in the supply of domestic flights between all 50 U.S. states.

Data concerning the dates and type of travel restrictions implemented by state governments was collected using the Johns Hopkins University U.S. state level policy tracker and GitHub repository (Figure 1). This information is publicly available through the JHU Coronavirus Resource Center page. COVID-19 case count data, which included the weekly number of COVID related and overall deaths within the United States, was downloaded from the Centers for Disease Control and Prevention (CDC) public data catalog.

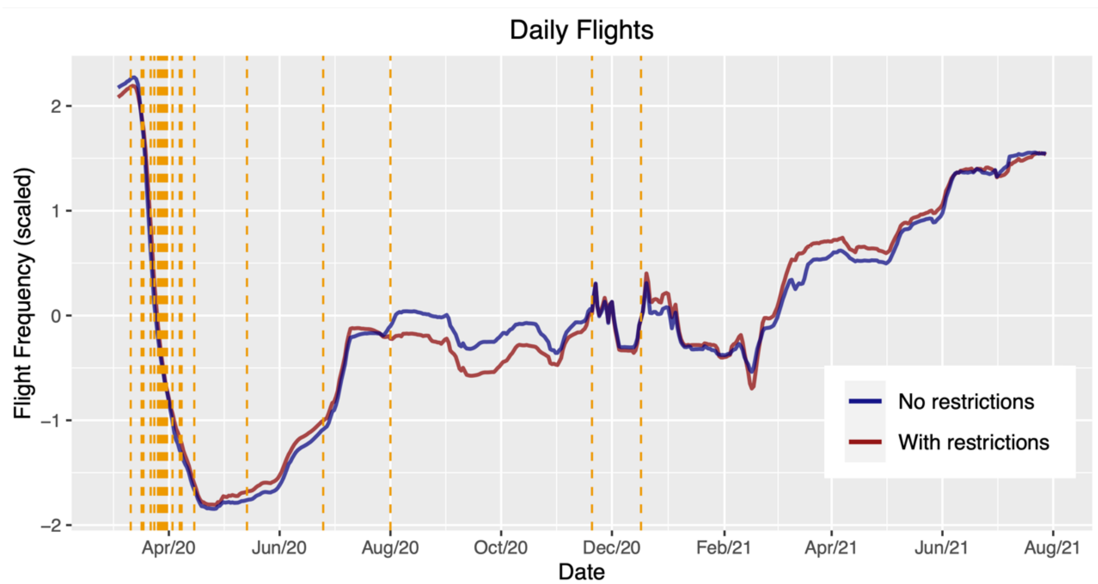


Figure 2: Comparing changes over time in daily flight frequency between the 27 U.S. states who issued travel restrictions and the 23 that did not. Vertical dashed lines represent dates in which travel restrictions were put in place. Flight frequency is scaled and computed using a 7-day rolling average to allow for more fair comparison.

Regression Discontinuity Design (RDD)

To examine the impact of a travel restriction on the number of flights to selected U.S. states, a regression discontinuity design (RDD) model was adopted. Regression discontinuity design is a quasi-experimental pretest-posttest design that aims to determine the causal effects of interventions by assigning a cutoff or threshold at the point when an intervention is assigned. The general idea of this method is to use the observed outcome at a time beyond *c* (such as the specific time when a travel restriction is established) by a small margin to estimate the outcome on the other side of *c* to calculate the resulting effect of the treatment (Lee and Lemieus, 2010). RDD takes advantage of an abrupt difference in treatment assignments and is widely applicable in a rule-based world, with strength in its internal validity (Cook, 2008). RDD is therefore a valuable method for researchers interested in assessing the causal effects of policies.

In order to apply this methodology to daily flight frequency data, a dummy variable, *threshold*, was computed to indicate whether a date is before or after the date in which a travel restriction was put in place. The dummy classifies the data points—threshold is equal to zero for observations below and equal to one for observations above the cutoff. Next, a linear model was specified with the function *lm( )* to regress the number of daily flights on the *threshold* dummy and the observation's date. The intuition comes from the assumption that points closest to the cutoff will be very similar, i.e one day before verses one day after the cutoff. However, one date will be during a restriction while another will not. Comparing the value of the restricted dates (treatment group) to the counterfactual outcome of the non-restricted dates (control group) will then deliver the local treatment effect. In other words, the model calculates whether a date being within a restricted time period has any effect on the number of departing flights flown on that particular day.

Dates are centered around the cutoff value by subtracting the restriction date from each date bin with the help of the *I( )* function. *I( )* serves two purposes; first, to convert the class of the object within the parenthesis to "as.is," and second, to isolate arithmetic operators such as "^" or "-" and prevent them from being interpreted as a formula. In the RDD algorithm, it is used to both center the dates around the threshold value and apply the quadratic form to the flight frequency data.

Gelman and Imbens (2019) argue that controlling for high order polynomials of the forcing variable can be misleading, as these models may identify positive treatment affects when the true relationship between the data is not linear. Instead, they recommend instead using only polynomials up to the second degree. Given the non-linear nature of the data used in this analysis, a quadratic relationship was applied to the functional form on either side of the cutoff. The model then evaluates how these two trends differ and presents the treatment effect of the cutoff using the coefficient of the dummy variable *threshold*. See appendix for more details.

RDD models have two main assumptions. First, a defined cutoff point or threshold, and second, that that all potentially relevant variables, excluding the treatment and outcome variable, are continuous at the point where a discontinuity occurs. The specific dates at which travel restrictions were put into place serve as a well-suited threshold point, satisfying the first assumption. The second assumption is more complex. One should first consider that trends in air travel, although subject to significant fluctuation throughout the pandemic, are similar on average in the short term. This analysis therefore operates under the premise that other variables that can impact flight frequency were continuous both before and after the start date of a travel restriction. This assumption is noted and expanded upon further in the limitations section of this paper.

A major benefit of using non-parametric methods in an RDD is that they provide estimates based off data closer to the cut-off, reducing bias that may otherwise result from using data farther away from the cutoff to estimate local treatment effects. This is intuitively appealing, especially considering the stochastic nature of the data used in this analysis. It eliminates some worry surrounding the potential issues that come with applying statistical models to trends that are as random and unpredictable as the ongoing COVID-19 pandemic. Regardless, data was filtered to include only the 30 days before and after a travel restriction was put in place. As more information was revealed about the way the virus behaves and how to best contain its spread, recommendations made by the federal government and organizations like WHO and the CDC changed significantly. Filtering the data further controls for the variability in potentially confounding factors that was observed over the course of the pandemic.

Detrended Time Series Analysis

Although regression discontinuity design models provide meaningful insight into the significance of treatment effects, it remains impossible to make true causal inference with this method alone. As discussed above, the model does not automatically reject causal effects by potential confounding variables. It is important to note that individual travel behaviors were very likely influenced significantly by the severity of the pandemic, regardless of any travel restrictions that may or may not be in place during a given date.

With this in mind, the lag time between policy interventions and changes in state flight frequency were analyzed. In order to account for the non-stationarity of the data, seasonality and overall trends were decomposed using nationwide flight frequency data and extracted to detrend individual, state level time series objects. Time series decomposition is a mathematical procedure that works by splitting a time series into three components: seasonality (patterns that repeat over a fixed period), trends (the underlying pattern), and random fluctuation. Although there was a significant decline in flight frequency at the beginning of the pandemic, recovery has generally been positive since then. Because of this, a multiplicative model was used to conduct the decomposition. First, the underlying trend was detected using a centered moving average and removed to expose seasonality. Then, seasonality was averaged and again removed, leaving behind only random noise.

A Pruned Exact Linear Time (PELT) change point detection algorithm was subsequently applied to each random noise model to estimate, with underlying trends removed, the number and frequency of change points in the data. Changepoint analysis is a valuable method, used to identify points within a dataset where the statistical properties change (Wambui et al, 2015). The PELT algorithm detects changepoints through minimizing a cost function over possible numbers and locations of changepoints. This method is both more accurate than binary segmentation and faster than other exact search methods (Wambui et al, 2015). The results of the change point detection algorithm were compared with the points in which travel restrictions were implemented to assess the potential effects of interventions adopted by individual states on future flight frequency. If the start date of a travel restriction has a significant effect on the number of daily incoming flights in a state, regardless of trends observed at the national level, this change-point detection algorithm would recognize this change and return a date within a few days following the start date (See Figure 2 and Figure 4).

Specifically, this study is interested in where and to what extent state flight frequency trends differed from those observed in the overall population. Data was standardized and a 7-day rolling mean was computed to allow for fair and accurate comparison, and visual aids were developed in addition to statistical tests to assist readers in understanding how policies varied between states and how they might have had an impact on flight frequency within that state.

RESULTS:

Regression Discontinuity Design:

RDD Model Results				
State	Multiple R-squared	Adj. R-squared	p-value	Threshold
Effective				
Florida	0.99	0.99	2.20×10^{-16}	-303.99
Idaho	0.96	0.95	2.20×10^{-16}	-0.93
New Jersey	0.96	0.95	2.20×10^{-16}	-12.81
New Mexico	0.96	0.96	2.20×10^{-16}	-2.23
New York	0.92	0.91	2.20×10^{-16}	-4.77
Texas	0.98	0.98	2.20×10^{-16}	-92.81
Not effective				
Alaska	0.90	0.88	2.20×10^{-16}	5.82
Arizona	0.97	0.97	2.20×10^{-16}	35.19
Arkansas	0.20	0.13	3.34×10^{-2}	0.30
Connecticut	0.70	0.68	2.20×10^{-16}	3.96
Kentucky	0.96	0.96	2.20×10^{-16}	20.98
Maine	0.96	0.95	2.20×10^{-16}	8.71
Maryland	0.46	0.41	1.95×10^{-6}	70.11
Massachusetts	0.23	0.16	1.10×10^{-2}	10.94
Montana	0.97	0.97	2.20×10^{-16}	2.97
North Dakota	0.95	0.94	2.20×10^{-16}	5.57
Oklahoma	0.96	0.96	2.20×10^{-16}	9.01
Pennsylvania	0.08	-0.01	4.81×10^{-1}	43.27
Rhode Island	0.97	0.97	2.20×10^{-16}	3.76
South Carolina	0.97	0.97	2.20×10^{-16}	12.41
Utah	0.91	0.89	2.20×10^{-16}	15.43
Vermont	0.96	0.96	2.20×10^{-16}	4.17
West Virgina	0.91	0.90	2.20×10^{-16}	4.50
Wyoming	0.92	0.91	2.20×10^{-16}	4.73

Figure 3: Results of RDD analysis, where the functional form is modelled using a quadratic relationship between flight frequency counts and date and assuming different slopes around the cutoff.

The model was run on each state using the date that their travel restrictions were put in place as the respective threshold. The results suggested that the following six states saw a significant decline in flight frequency following the implementation of a travel restriction: Florida, Idaho, New Jersey, New Mexico, New York, and Texas (Figure 3). The coefficient of the dummy variable threshold represents the average treatment effect. A negative value represents a fall in the number of daily flights after the date in which a travel restriction was implemented. On the other hand, a negative value indicates that the number of daily flights increased after the cutoff. A quadratic functional form was assumed in this analysis, as it maximized R^2 and fit metrics for the flight frequency data and best mimicked the visual tends observed during the initial exploratory analysis.

Time series analysis:

Once the six states whose travel restrictions may have had a positive and significant effect on domestic flight frequency were identified, an analysis of time series data was conducted. The goal of this analysis was to uncover further insight into the relationship and while assessing the reliability of the RDD model. Before detrending the data and implementing the PELT changepoint algorithm, a short exploratory analysis was conducted to assess the correlation between national and state level trends in flight frequency (Figure 4). Although the visual shows periods where the two vary, their overall shape of the two groups remains the same. Of the six states analyzed, there was not an observable change within the time period in which a travel restriction was in place. Theoretically, a decrease in flight frequency after a travel restriction was implemented would result in a visual discrepancy between the state (green) and aggregate national trends (grey). This is not true for any of the six figures, suggesting that we should be weary of the results of the RDD model, which did not take into account national trends in flight frequency. Regardless, time series objects for each state were decomposed and detrended in order to see if changes would become more obvious when the data is more stationary.

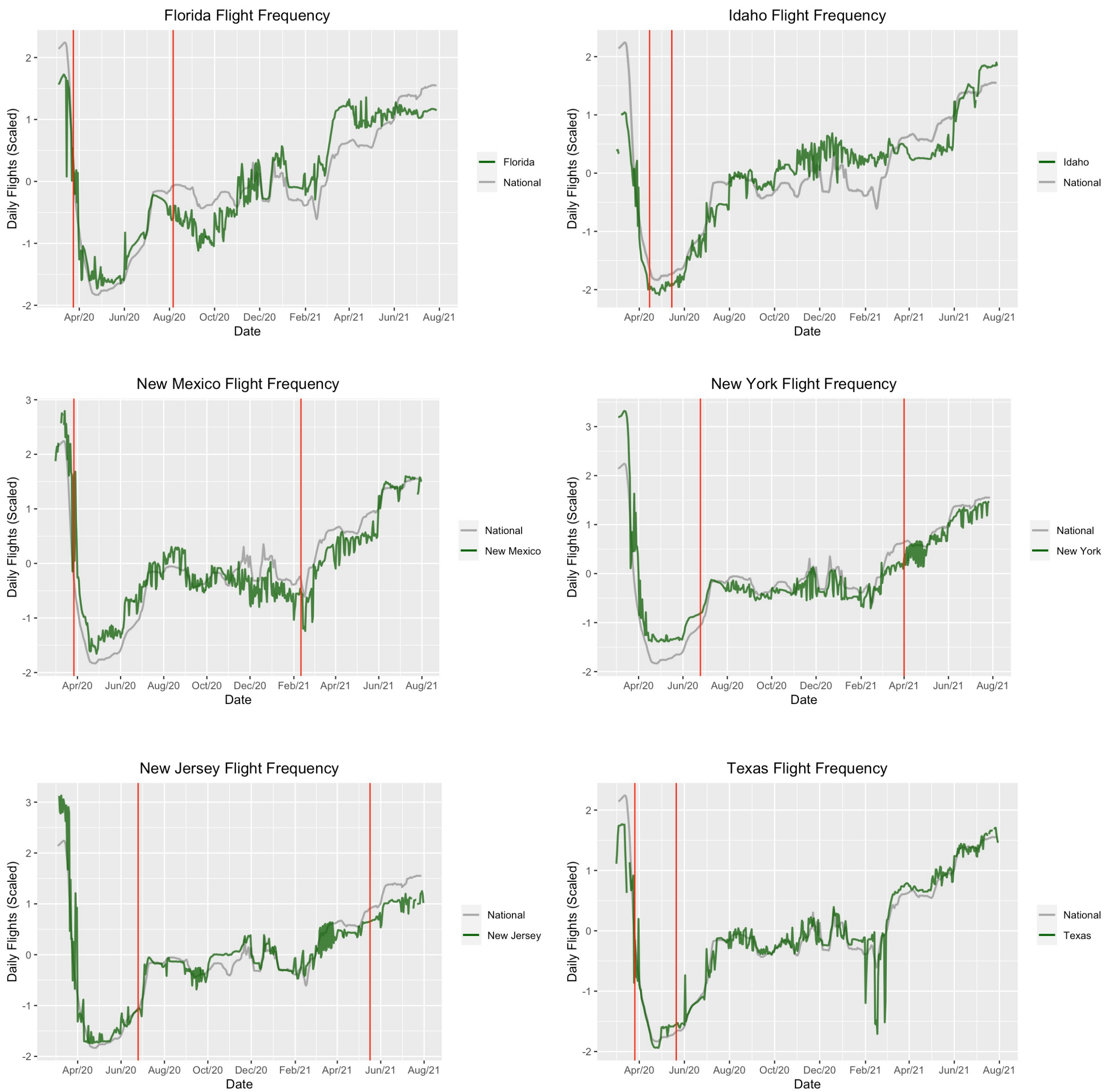


Figure 4: Comparing trends in state level (green lines) versus national flight frequency (grey lines). Flight frequency is scaled and computed using a 7-day rolling average to allow for more fair comparison. Vertical red lines represent dates when travel restrictions were enacted and rescinded.

After using national flight frequency trends to detrend the time series of individual states (Figure 5) and accounting for weekly seasonality, random noise is left behind. Now, a changepoint function can be used to calculate sudden shifts in the data that differ from the trends observed nationally. The function identified two to three changepoints for each of the six states.

This method did not identify a sudden shift in flight frequency at dates within a few days after a travel restriction was implemented in a respective state. Curiously, this analysis returned a significant change point in New Mexico on 3/24/2020, three days before a travel restriction was put in place, and in New Jersey on 6/25/2020, ten days before a travel restriction was put in place. This suggests that there may have been other events within the state that prompted a decrease in flight frequency before a restriction was made official. These findings do not support the results of the RDD analysis and suggest that any significant decrease in flight frequency following the beginning of a travel restriction is likely due to the presence of other confounding variables.

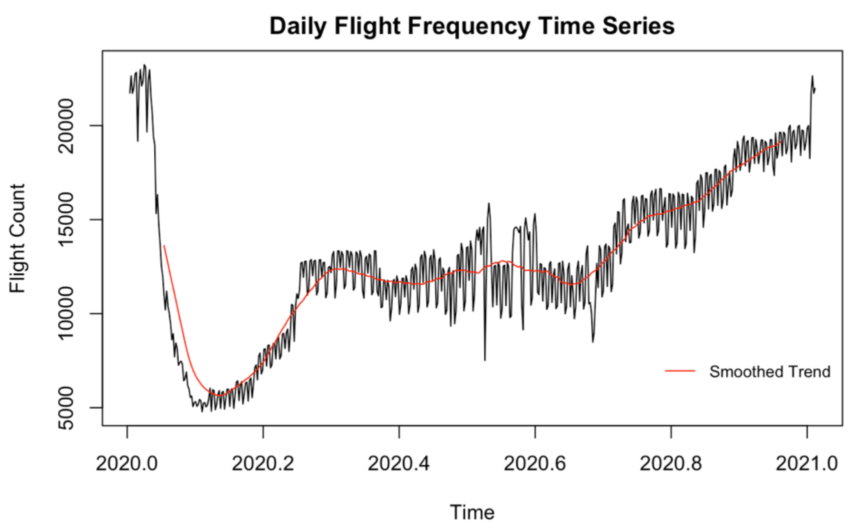


Figure 5: Time series object showing the national trends in flight frequency from March 1, 2020, to July 31, 2021. Red line represents the trend extracted from this data to detrend that of the individual states.

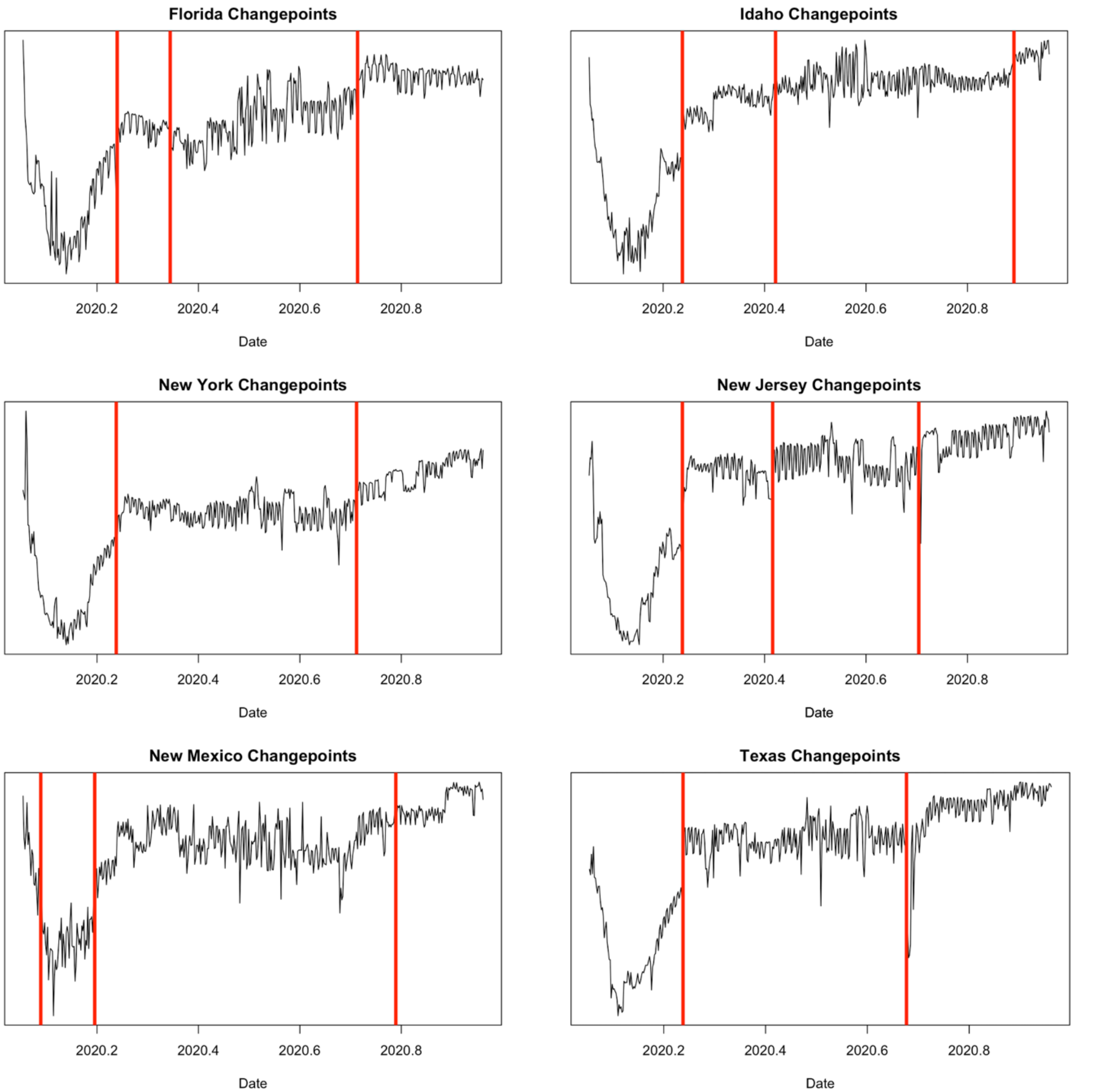


Figure 6: Changepoints identified using individual detrended timeseries data. Red vertical lines represent the point at which there is a sudden shift in the observed trend. This includes Florida (6/5/2020, 8/15/2020, 2/8/2021), Idaho (6/4/2020, 9/16/2020, 5/21/2021), New Mexico (3/24/2020, 5/17/2020, 3/17/21), New York (5/1/2020, 2/9/2021), New Jersey (6/15/2020, 9/27/2020, 1/4/2021) and Texas (6/5/2020, 1/17/2021).

Limitations/Ethical Considerations

Assessing the impact of a real-world travel ban is challenging. Travel bans are often implemented alongside other travel restrictions and control measures, making it difficult to tease apart the impacts of travel bans verses other outbreak response measures. This study is based on models that naturally come with assumptions, variance and inaccuracies that make them unable to account for things like culture or human behavior. In addition, social and environmental circumstances also influence how a disease is transmitted. For example, people may have voluntarily reduced their travel or changed their modes and routes of transportation in response to increases in the severity of the pandemic. Together, these factors have an impact on how or if control measures work, making it difficult to apply the conclusions form any given study to the novel coronavirus. The aim of this research is to provide insight into the potential contributions of travel restrictions and help guide future policymakers and government officials in the case that the country is faced with a similar crisis in the future.

DISCUSSION

Considering the near universal adaption of travel-related restrictions, especially in light of their potentially large economic and social consequences, this study aimed to understand whether such measures can be, and have been, effective at reducing the frequency of interstate air travel during the recent coronavirus pandemic. Using RDD models and time series analysis techniques, this research found little evidence that state issued travel restrictions significantly reduced commercial flight frequency in the United States.

Although the RDD model identified six states whose travel restrictions may have led to a significant decrease in the number of daily arrivals (Florida, Idaho, New Mexico, New York, New Jersey and Texas), these findings were not supported by the subsequent time series analysis. The results of this study prematurely suggest that COVID-19 case counts have had a more significant impact on of flight frequency than the presence or absence of a travel restriction. While a reduction in travel and human activity is unequivocally a decisive factor when it comes to the extent and speed in a which a transmissible disease is spread, the impact of travel restrictions on reducing this mobility is not well supported. Travel restrictions were a popular approach taken by policymakers hoping to reduce activity and restrict the movement of potentially infected people. It is therefore warranted to assume that these policies were put in place to decrease travel in a way that would lead to a subsequent decline in the spread of the novel coronavirus. Thus, assessing the impact of a travel restriction on interstate travel is the first step in understanding how government policies can influence the scope and spread of a highly transmissible disease.

Similar studies have found very low-certainty evidence that cross-border travel controls and can slow the spread of COVID-19. Most studies have reported slight positive effects, in terms of a reducing in travel or a reduction in coronavirus case counts, with effect sizes varying widely. A review by Grepin et al., (2020) identified 36 studies, of which 25 were specific to COVID-19 and concluded with low to very low certainty that cross-border travel measures may limit the spread of disease across national borders, specifically in terms of delaying or reducing epidemic development. Additional evidence suggests that a travel ban may delay the arrival of an infectious disease in a country by days or weeks. However, there is very little evidence to suggest that a travel ban eliminates the risk of the disease crossing borders in the long term (Errett et al., 2020). Errett concludes that there is an urgent need for additional research to inform policy decisions on the use of travel bans and other control measures to control emerging infectious diseases in advance of the next outbreak.

Using a meta-population model based on temporal networks and calibrated on COVID-19 data in Italy, Parino et al., (2021) did not find evidence of travel restrictions preventing the spread of COVID-19. They argue that, if a travel restriction is not implemented in the early phases of the outbreak, policymakers should prioritize activity reduction polices instead.

Likewise, Burns et al., (2020) found very low-certainty evidence at best to support the hypothesis that cross border travel restrictions lead to a reduction in travel volume a new coronavirus cases. Burns suggests that the effects of a travel-related quarantine are likely to depend on factors such as the stage of the epidemic, the interconnectedness of countries, local measures undertaken to contain community transmission, and the extent of implementation and adherence.

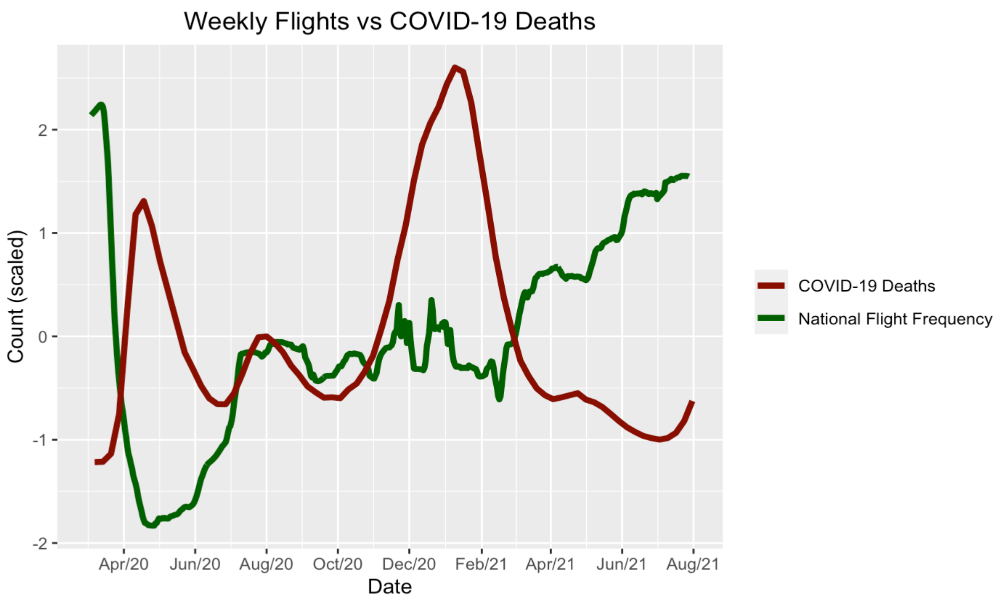


Figure 7: Trends observed over time in total COVID-19 deaths in comparison to national flight frequency counts. Both variables are calculated using a monthly rolling average and scaled to allow for more fair comparison.

There is clearly a relevant relationship between commercial air travel and COVID-19 case count data. Figure 7 shows that these two variables had the strongest correlation during the first half of 2020, around the same time period that many state governments issued travel restrictions. This relationship became less relevant over time as the behavior of the general population became less sensitive to changes in the overall severity of the pandemic. Investigating this interaction further at both the statewide and nationwide level would be a reasonable next step. Given the number of potential confounding variables as we as the unpredictability and unprecedented nature of the coronavirus pandemic, the questions rising from this potential relationship are outside the scope of this analysis. Likewise, this analysis could be supplemented with data concerning other methods of travel, such as interstate travel by personal cars. More specifically, to what extent have decreases/increases in all modes of interstate travel affect the number of positive COVID-19 cases within individual states? Differences in social and environmental circumstances between states may have contributed to an individual's decision to abide to travel restrictions, potentially decreasing the effectiveness of these policies. Additional research into the cultural implications of the effectiveness of travel bans could help explain the results of this study, as well as others.

Travel restrictions make business travel, access to social support systems and the movement of healthcare personnel substantially more difficult. This can cause unnecessary disruptions to overall mental, physical, and economic health. In the future, researchers may want to explore the economic and social effects of these travel restrictions to determine how they might have contributed to the economic losses suffered by individual states during the pandemic. This would be particularly applicable to state's whose economies rely heavily on the success of their travel industry, such as Nevada and Hawaii, and build a more complete understanding of the opportunity cost of enacting such restrictions.

The results of this study suggest that travel restrictions, issued in the form of executive orders, have not been effective in decreasing domestic air travel in the United States. Their influence is minimal at best. This is true for restrictions that applied to all travelers and those that applied to only a subset. Although a two-week mandatory quarantine was the most common approach, these findings also suggest that no specific mandate was significantly more effective at decreasing interstate travel. Unless there are significant changes in federal laws that allow states more power to restrict travel or increase the consequences of breaking these restrictions, this research suggests that travel restrictions are not an effective intervention to decrease the amount of interstate travel.

These findings can provide insight to state governments on where they should focus their efforts when it comes to minimizing the effects of a pandemic. Instead of devoting time and resources to the implementation and enforcement of travel restrictions, policy makers should consider redirecting their attention towards measures proven to be effective. This could also include investing in their public health systems and preparing health systems to deal with a potential future outbreak. Travel bans put significant pressure on state economies and communities, but there is little evidence to suggest that they influence commercial air travel. In addition, a causal relationship between travel restrictions and the spread of disease is unlikely. Until more evidence is available government officials should use extreme caution in applying travel restrictions as a means to control the spread of disease. Should a crisis of this scale ever reach the United States again, understanding the relationship between the coronavirus pandemic and the vast commercial aviation industry will be essential to minimizing and preventing further harm.

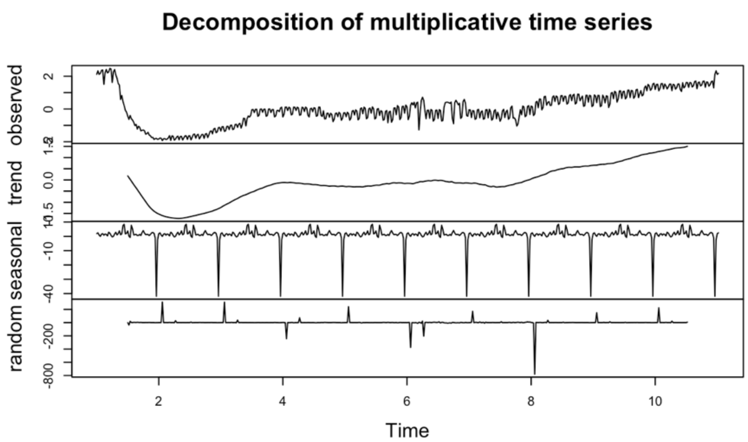
APPENDIX

RDD model code:

```
# ALASKA
ak_all$date = as.numeric(ak_all$date)
ak_lm30q <- ak_all %>%
  filter(date >= 18302 & date <= 18362) %>%
  mutate(threshold = ifelse(date >= 18332, 1, 0)) %$%
  lm(flightscount ~ threshold + I(date-18332) + I((date-18332)^2) + threshold:I(date-18332) +
threshold:I((date-18332)^2))

summary(ak_lm30q)
```

Time series analysis details:




```
```{r}
# STEP 1: DETECT THE TREND
trend_states = ma(statets, order=52, centre =T)
plot(as.ts(statets), ylab = "Flight Count", main = "Daily Flight Frequency Time Series")
lines(trend_states, col = "red")
legend(2020.77, 8000, legend = c("Smoothed Trend"), col = c("red"), lty = 1:1, cex = 0.8, box.lty = 0)
```
```

```
```{r}
# STEP 2: DETREND THE TIME SERIES
detrend = statets / trend_states
plot(as.ts(detrend), ylab = "Flight Count", main = "Detrended Time Series - All Flights")
```
```

```
```{r}
# STEP 3: AVERAGE THE SEASONALITY
m_air = t(matrix(data = detrend, nrow = 52))
seasonal_allflights = colMeans(m_air, na.rm = T)
plot(as.ts(rep(seasonal_allflights,52)))
```
```

```{r}
# STEP 4: EXAMINING REMAINING RANDOM NOISE

random_allflights = statets / (trend_allflights * seasonal_allflights)
plot(as.ts(random_allflights))

# detrending the individual states using national trends
random_ak = akts / (trend_allflights * seasonal_allflights)
random_az = azts / (trend_allflights * seasonal_allflights)
random_ar = arts / (trend_allflights * seasonal_allflights)
random_ct = ctts / (trend_allflights * seasonal_allflights)
random_fl = flts / (trend_allflights * seasonal_allflights)
random_id = idts / (trend_allflights * seasonal_allflights)
random_ky = kyts / (trend_allflights * seasonal_allflights)
random_me = mets / (trend_allflights * seasonal_allflights)
```

The Changepoint Model:

We assume that we have been given a cost function C(.) and some penalty term, B, used to avoid overfitting. Then, to detect change points, we wish to optimize over the following equation, where the vector of changepoint locations is then given by τ.

$$\min_{\tau,k}\left[\sum_{j=0}^{k} \mathcal{C}(\mathbf{y}_{\tau_j+1:\tau_{j+1}}) + \beta\right],$$

The PELT method modifies the commonly used multiple changepoint detection method by pruning to achieve exact and efficient computational cost, which is linear in the number of observations (n).

$$F(n) = \min_{\tau_m}\{ F(\tau_m) + C(y_{\tau_m+1}, \ldots, y_n) \}$$

The algorithm begins by calculating F (1) and then recursively calculating F (2), … , F(n). At each step the optimal segmentation is stored. When F (n) is reached, the optimal segmentation for the entire data has been identified and the number and location of changepoints is then recorded. The benefit of pruning is to remove those values of τ that can never be minima at each iteration. (Wambui et al, 2015)

```{r}
# DETECTING CHANGE POINTS
```

```{r}
# FLORIDA

flcp <- cpt.var(na.omit(random_fl), method = "PELT")
plot(flcp, type = "l", cpt.col = "red", xlab = "Index", cpt.width = 4, main = "Florida Changepoints")
cpts(flcp)

fl_all %>%
  select(date, flightscount) %>%
  mutate(growth = 100 * ((flightscount / lag(flightscount)) - 1)) %>%
  filter(date > "1960-01-01") %>%
  slice(cpts(flcp))
```

GITHUB REPOSITORY: https://github.com/jessicamhop/hopkinsda401

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