How departure delays at airports affect one another

Problem and Data Structure

For my capstone I was interested in examining how departure delays at one airport can have system wide effects on departure delays from other airports in the United States. There are 5,217 public airports in the United States[2] but about 80% of passengers flying are through the top 50 public U.S airports. Data from the Bureau of Transportation Statistics on flights between 2018 and 2024 was collected for the top 50 public U.S airports. The data was then formatted by the number of departures delays 15 minutes or more at a given hour all the way till 2024.

Methods

To decide how many lags to consider I considered 4 key metrics AIC, (Akaike Information Criterion which measures the quality of a model compared to others while accounting for number predictors – lower AIC is better.), SC, (Schwarz Criterion also more commonly known as BIC, it is a metric like AIC but more conservative regarding model complexity), HQ, (Hannan–Quinn information criterion which is like AIC and SC but in between both in terms of conservativity), and final prediction error (FPE). Lags from 1-20 hours were evaluated.

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$selection
AIC(n)  HQ(n)  SC(n) FPE(n)
    20     10      5     20

$criteria
                  1            2            3            4            5            6            7            8            9           10
AIC(n) 5.528179e+01 5.196570e+01 5.082827e+01 5.011910e+01 4.963102e+01 4.932732e+01 4.911811e+01 4.891748e+01 4.874255e+01 4.860728e+01
HQ(n)  5.540991e+01 5.221943e+01 5.120760e+01 5.062404e+01 5.026157e+01 5.008348e+01 4.999987e+01 4.992485e+01 4.987552e+01 4.986587e+01
SC(n)  5.569273e+01 5.277953e+01 5.204498e+01 5.173869e+01 5.165350e+01 5.175269e+01 5.194636e+01 5.214861e+01 5.237657e+01 5.264418e+01
FPE(n) 1.019944e+24 3.701842e+22 1.186965e+22 5.840489e+21 3.584936e+21 2.645983e+21 2.146492e+21 1.756296e+21 1.474443e+21 1.287911e+21
                 11           12           13           14           15           16           17           18           19           20
AIC(n) 4.850336e+01 4.841325e+01 4.834824e+01 4.827832e+01 4.819533e+01 4.811665e+01 4.803635e+01 4.794713e+01 4.783742e+01 4.773350e+01
HQ(n)  4.988755e+01 4.992305e+01 4.998364e+01 5.003933e+01 5.008194e+01 5.012887e+01 5.017419e+01 5.021057e+01 5.022646e+01 5.024815e+01
SC(n)  5.294314e+01 5.325592e+01 5.359379e+01 5.392676e+01 5.424665e+01 5.457085e+01 5.489345e+01 5.520710e+01 5.550028e+01 5.579925e+01
FPE(n) 1.160792e+21 1.060785e+21 9.940217e+20 9.269117e+20 8.531006e+20 7.885655e+20 7.277404e+20 6.656354e+20 5.964855e+20 5.376287e+20
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Figure 1. Results among criteria for different lags

Between the different criteria models of varying sizes from 5, to 20 were reported by differing models. Another factor to consider was the model size, as with 50 airports and lags of closer to 20, the dimensionality for the model would be massive and could risk overfitting. I decided with 6 lags as each of the criteria were decently minimized by that point and there would not be too many parameters given my dataset. To model departure delays I proceeded with a vector autoregression model with 6-hour lags (VAR(6)).

Results

To examine the performance of the VAR(6) model I looked at the RMSE between the actual amount of departure delays at a given hour and the predicted amount of departure delays at a given hour among the 50 airports. I did this procedure from predicting 1 hour ahead up till predicting 96 hours ahead (4 days).

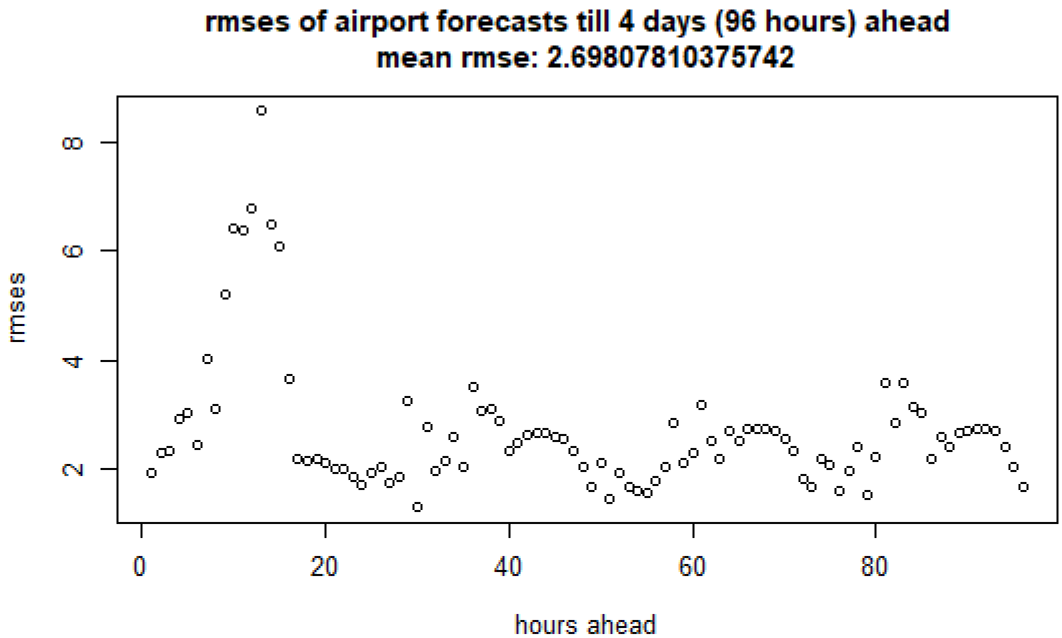


Figure 2. VAR(6) performance results

Despite an early jump in RMSE, which could be attributed to an actual shock delay event, the model performs relatively well and stable predicting up to 4 days ahead with a average RMSE of ~2.69 delays.

Due to the large amount of airports in the modeled system I decided to choose an airport close to George Mason University, DCA (Ronald Reagan Washington National Airport). To examine the influence of other airports versus DCA itself I used forecast error variance decomposition to compare the effects of shocks (increases in delays) at DCA itself vs shocks from other airports.

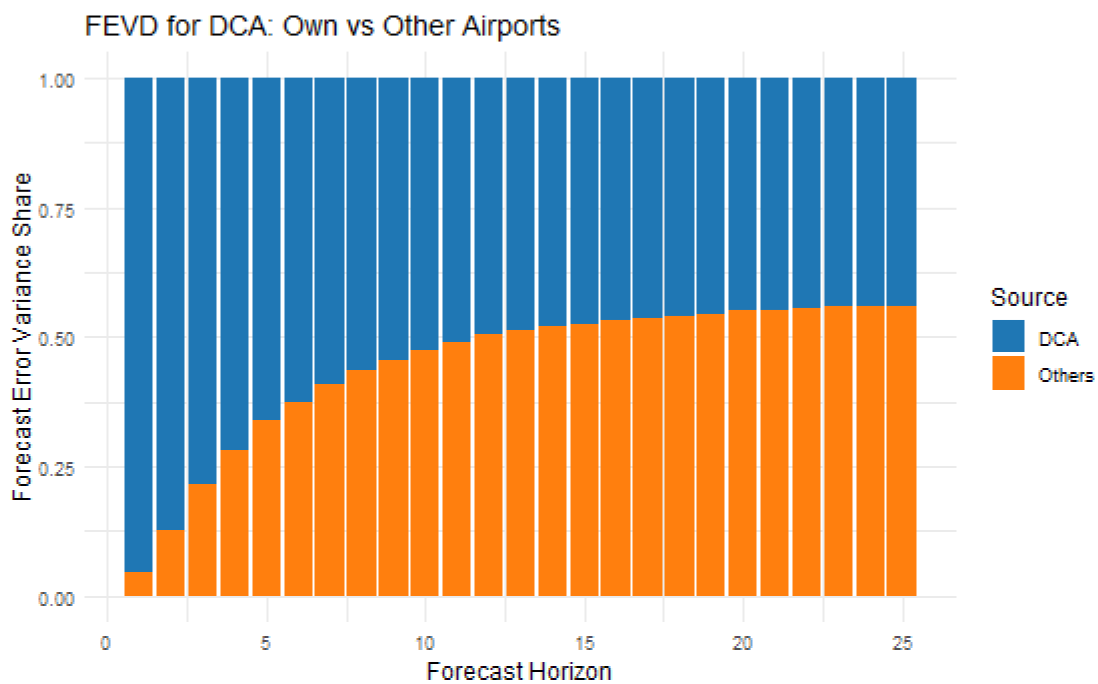


Figure 3. FEVD plot of DCA vs other airports, each forecast horizon is an hour.

From the plot, around hour 10, 50% of the variance of delays in DCA can be explained by the other 49 airports in the system. Individual airports each relatively had a small share, but this plot shows that combined, they can greatly affect delays for DCA. When examining the respective airport shares at each point, we found that BOS and LAX were the two most common contributors. This was expected from BOS as BOS is relatively close to DCA (Boston not too far from D.C) but was surprising for LAX as LAX is in California; this could be because delays at LAX may influence many other airports that are common for DCA to have connecting flights to.

To examine the spillover effect of departure delays with DCA, I conducted a delay shock simulation. To construct this simulation, I first predicted 24 hours ahead of delays, and then for DCA in the last hour I added 10 delays and then predicted 24 hours ahead again. The increase/decrease of delays is calculated by subtracting corresponding values from both the normal predictions and the predictions with the +10 delays in the last hour at DCA

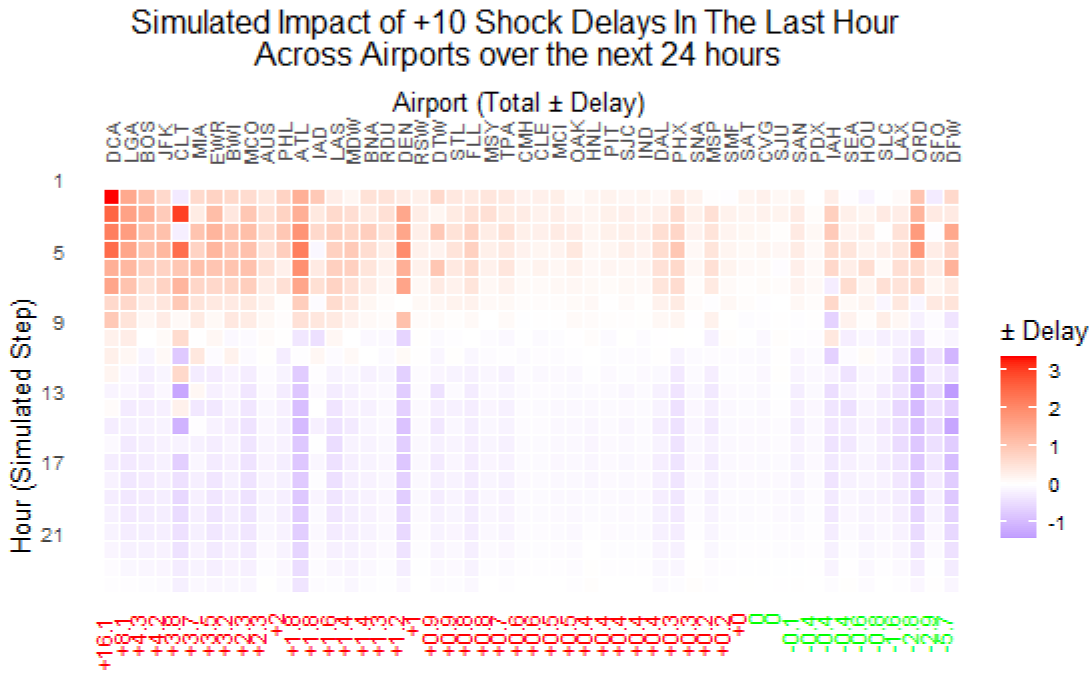


Figure 4. Increase/Decrease simulation results with change in delays on bottom and airport on top.

From this plot, as expected, DCA increases with the most departure delays over the next 24 hours, with an increase of 16.1 delays. Also, as expected, BOS will rise to 4.3 delays over the next 24 hours. A surprising thing to note is that despite LAX contributing a lot to the variance in delays at DCA in the FEVD, it had a decrease of 1.6 delays over the next 24 hours, including the +10 shock delays in the last hour. Additionally, DFW has 5.7 fewer delays over the next 24 hours, although, like the other airports, it also starts to have an increase in delays in the earlier hours (<9 hours). Overall, airports generally have an increase in delays over the next 24 hours when there is a +10-shock delay increase in the last hour at DCA. This simulation highlights the spillover effect of delays at one airport as it can also be seen that airport close to DCA, like LGA, BOS, and JFK, start to see an increase in delays before other airports, in addition to some airports also have a decrease in delays (this may also be because flights end up being redirected from that airport or cancelled due to delay pileup.)

When examining airports in general versus other airports the results are similar to that with DCA.

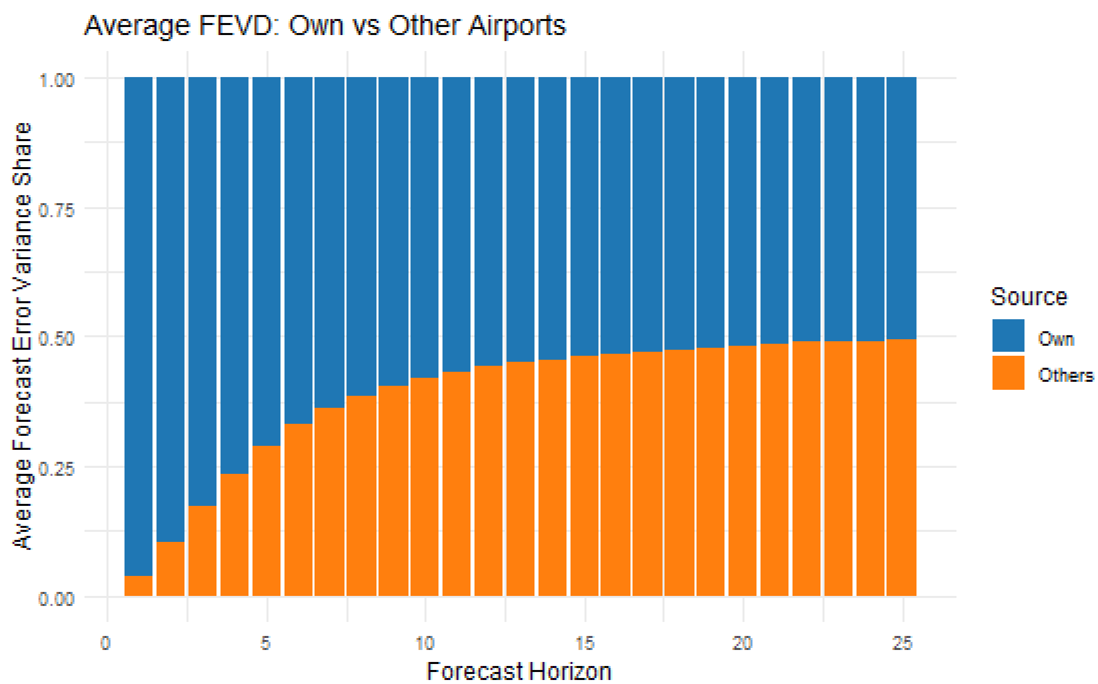


Figure 5. Average FEVD for airports vs other airports

Similar to DCA, it can be seen that on average around ~13 hours, 50% of the variance of delays at an airport can be explained by the other 49 airports in the system.

I also wanted to examine if flight traffic would also affect delays at an airport. To do this another VAR(6) model was constructed with exogeneous variables for hourly count of departures at each corresponding airport.

The performance of the model was better than without the exogenous variables, relatively well and continuous trend predicting up to 4 days ahead with a average RMSE of ~1.9 delays.

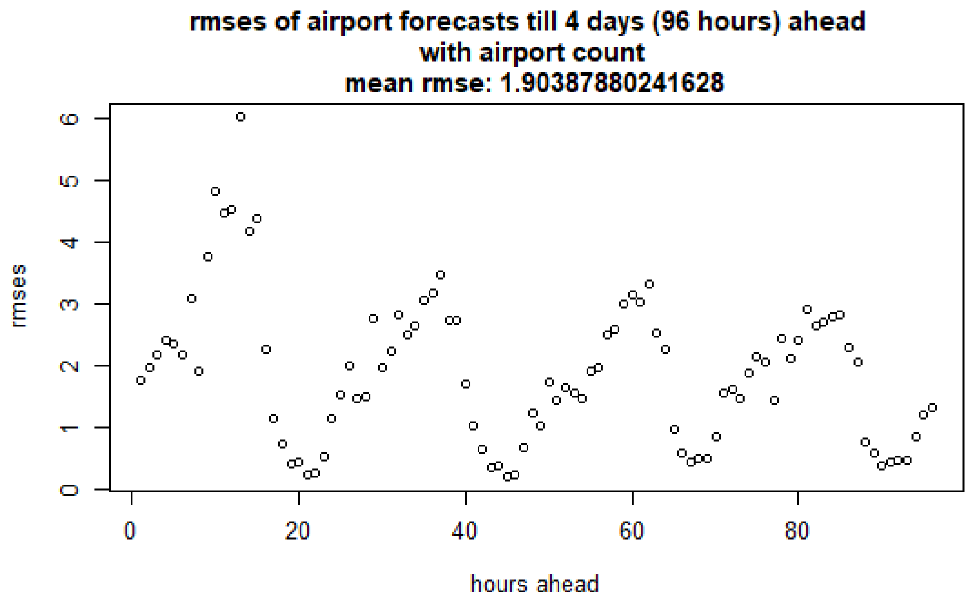
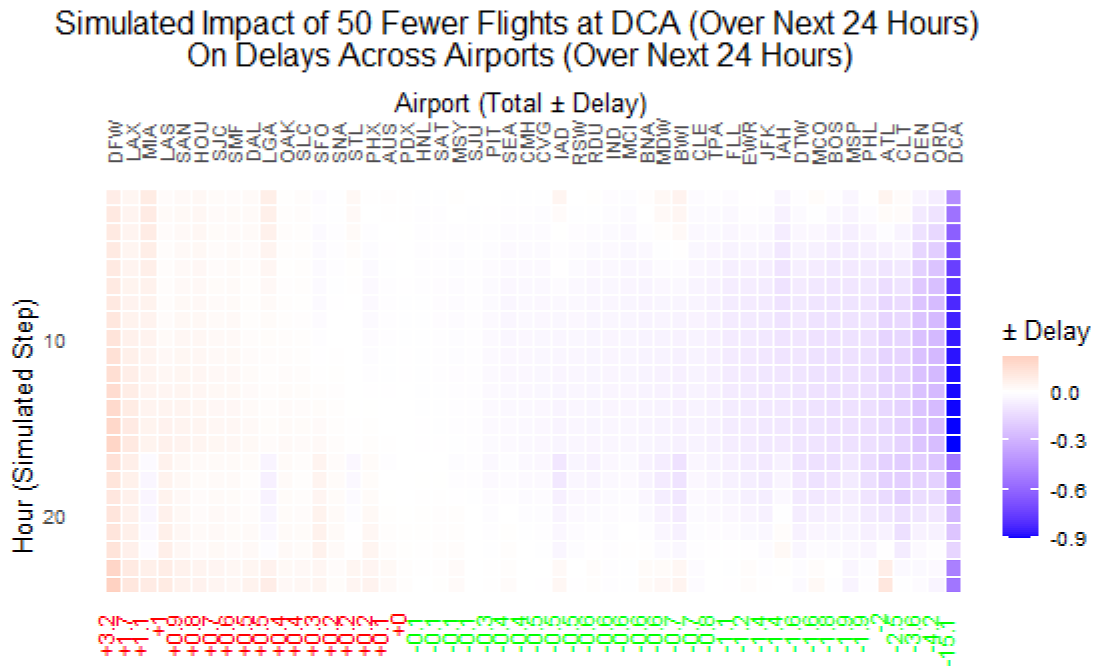


Figure 6. VAR(6) with exogenous variables performance results

To examine the flight traffic effect on departure delays I went with DCA, and I conducted a delay shock simulation similar to the one before. To construct this simulation, I first predicted 24 hours ahead of delays, and then for DCA over the next 24 hours I added 50 more flights and then predicted 24 hours ahead again. The increase/decrease of delays is calculated by subtracting corresponding values from both the normal predictions and the predictions with the +50 flights over the next 24 hours at DCA.



As expected DCA has the largest decrease in delays, with 15.1 fewer delays over the next 24 hours. Surprisingly rather than seeing BOS, the next airport with the largest decrease in delays is ORD with 4.2 less delays. DFW and LAX both increased in number of delays with 3.2 and 1.7 delays respectively, this is interesting because before it was observed that more delays would lead to a decrease in delays at DFW and LAX, but now a decrease in flights at DCA leads to an increase in delays. (This could be because when flights at DCA are reduced they might be redirected to other airports that connect to LAX or DFW.)

Conclusion

I set out to examine how departure delays at airports affect one another; I observed that, on average, by around ~13 hours approximately 50 percent of the variance in forecasted delays at an airport could be explained by past delays at that airport, and the remaining 50 percent from delays originating from other airports. Further, with DCA as the focus airport, it was observed how, in general, other airports would see an increase in delays when DCA suffers an increase, with airports closer to DCA having a more severe effect, but other airports can have a decrease in delays. It was also examined that including hourly departure flight traffic can build a more predictive model. Further, fewer delays over the next 24 hours at DCA generally lead to fewer delays among the top 50 airports, although some airports see an increase. These findings suggest a spillover effect among delays, but the effect is not constant; that is, while an increase in delays at one airport will generally lead to a rise in the rate of delays for about 10 hours, some airports can experience a decrease in delays. Further decreasing the number of flights at DCA will generally lead to fewer delays, but the effect still comes at a cost, as other airports will see an increase in delays.

References

1. *Passengers boarded at the top 50 U.S. airports*. (n.d.). Bureau of Transportation Statistics. https://www.bts.gov/content/passengers-boarded-top-50-us-airports.

2. Wikipedia contributors. (2025, April 16). Aviation in the United States. Wikipedia. https://en.wikipedia.org/wiki/Aviation_in_the_United_States#:~:text=Private%20aircraft%20are%20also%20used,general%20aviation%20and%20other%20activities.