A PREDICTIVE ANALYSIS OF AIRLINE PERFORMANCE METRICS' RELATION WITH CHANGES IN STOCK PRICE

CITADEL SECURITIES SUMMER INVITATIONAL DATATHON - TEAM 4

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1 Executive Summary

In the modern world, the airline industry is of paramount importance and interest. It serves as a cutting-edge transporter of people and goods, and is at the heart of the American economic engine. Given the importance and competition of the industry, it is important to better understand the factors that drive airline market success, and how firms and institutions can predict the market behavior of airlines. For these reasons, we chose to concentrate on the impact of various performance factors of an airline - how might these features, such as flights per month or monthly fuel costs, relate to stock prices? Are stock prices indeed strongly informed by the efficiency and productivity of an airline? These are curiosities which we set out to resolve.

From our investigation of the underlying factors in an airline industry we found the following:

1. Of the 8 airlines, Southwest Airlines was able to be predicted with the highest level of accuracy.
2. For most airlines, fuel costs (both international and domestic) are strongly correlated with stock price.
3. Stock price does not necessarily reflect all metrics that may seem important to a company's valuation, such as passenger flow, as shown by low correlation values.

2 Methodology

In order to begin our investigation of how the performance factors of an airline is reflected in the airline's stock price, we first sourced data on 9 different factors from the Bureau of Transportation Statistics (Table 1) in monthly intervals starting from October 2016 until April 2018. These dates were chosen in order to best align with the stock price data set that we were given.

After gathering the data on airline factors, we cleaned the data using the pandas library in order to best align it with stock price. In addition to cleaning the data on airline factors, we created various features with the stock data (see Appendix A.1). Due to time constraints, we were not able to incorporate these features into our investigation and model. Due to data availability, we chose to analyze the 8 airlines with included stock data.

We then ran a series of correlation calculations between each of these performance metrics and each airline's stock price. After determining which metrics are most strongly correlated with the stock price, we investigated using recurrent neural networks and convolutional neural networks to perform a predictive analysis using these most significant features. We chose a recurrent neural network, as it tended to preform much better. Finally, we used the model generated by the RNN to predict the stock price for testing data that was set aside from the provided dataset.

Table 1: Description of Airline Performance Metrics

Feature Name	Description
Available Seat-Miles	The number of seat miles available for purchase on an airline. Seat miles refers to the number of miles that a given airplane will be traveling multiplied by the number of open seats on that flight.
Baggage Fees	The total amount of revenue collected through baggage fees.
Flights	The number of flights flown domestically, internationally, and total.
Fuel	The domestic, international, and total consumption, cost per gallon, and cost of fuel.
Load Factor	The percentage of available seating capacity that has been filled with passengers.
Net Income	The net income the airline received.
Operating Revenue	The operating revenue the airline received.
Passengers	The total number of passengers who flew with the airline.
Revenue Passenger-Miles	The number of miles traveled by paying passengers.

2.1 Correlation Testing

For the sake of document simplicity, here we only present the most strongly correlated features for United Airlines. See the attached code for a more detailed overview of our correlation analysis across all airlines.

For United Airlines, we found that the international number of flights, number of international passengers, and the international available seat miles are the three most strongly correlated performance metrics with respect to United's stock price. In addition, we provided a weakly correlated metric, net income, to give some more perspective on the range of correlations. The strongly correlated metrics — number of international flights, number of international passengers, and number of international available seat miles —make sense considering that United is one of the largest international airline carriers, and thus a majority of its company performance is a product of its international performance. As mentioned in the executive summary, one weakly correlated metric, total net income, is interesting in that it suggests that stock price for United Airlines does not seem to depend as highly on cash flow.

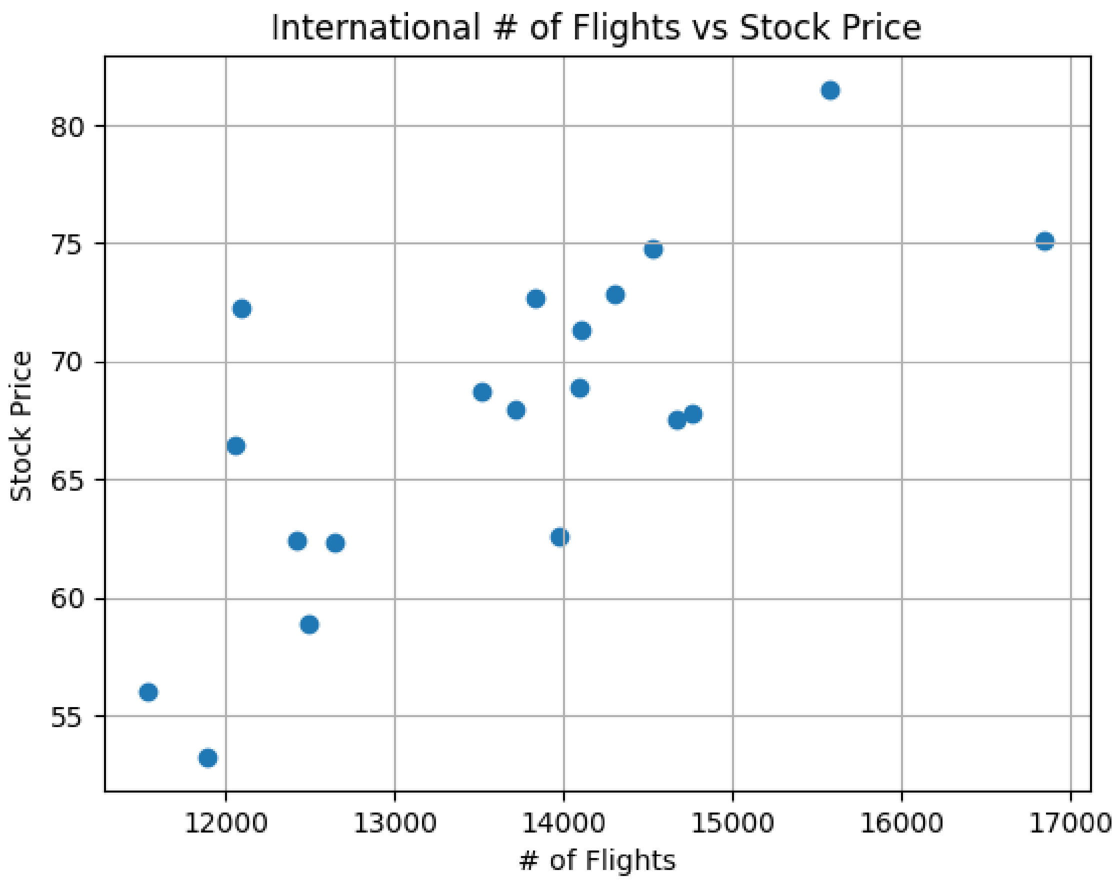

Figure 1: Correlation Coeff: 0.733

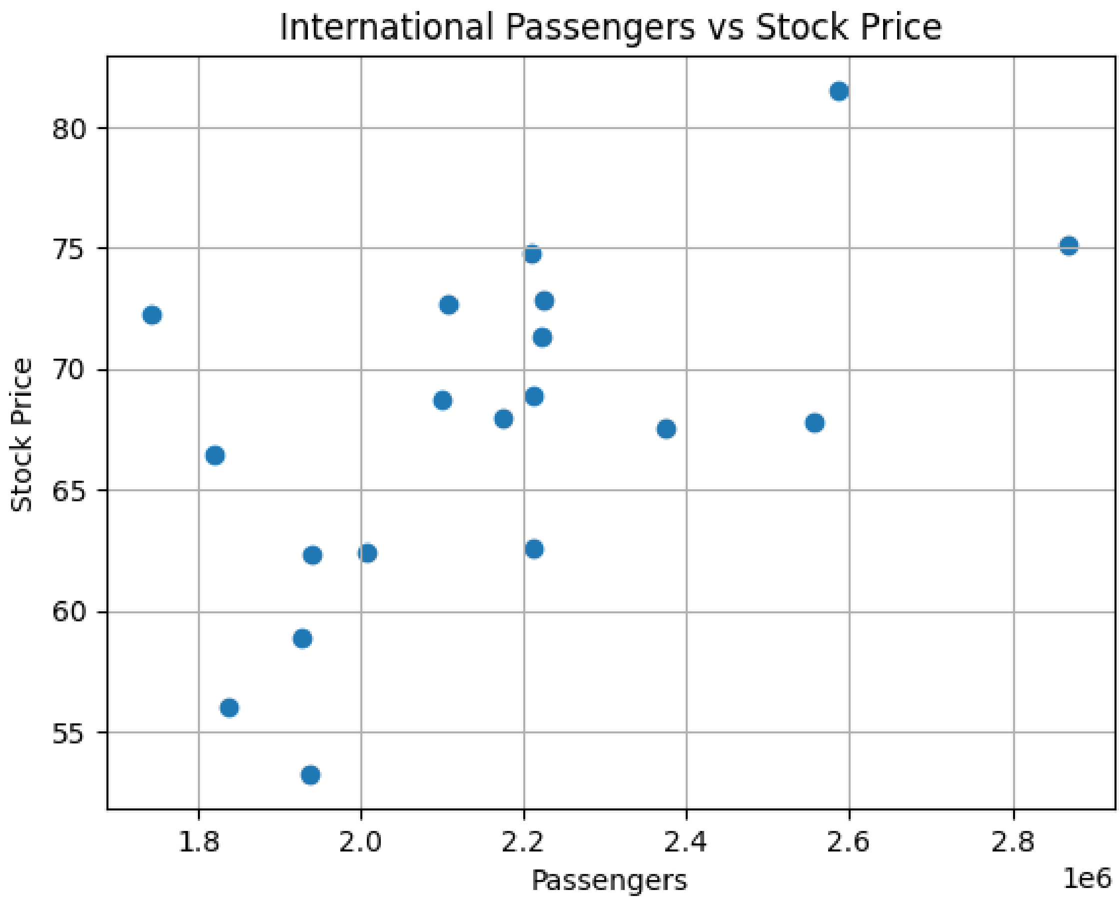

Figure 2: Correlation Coeff: 0.582

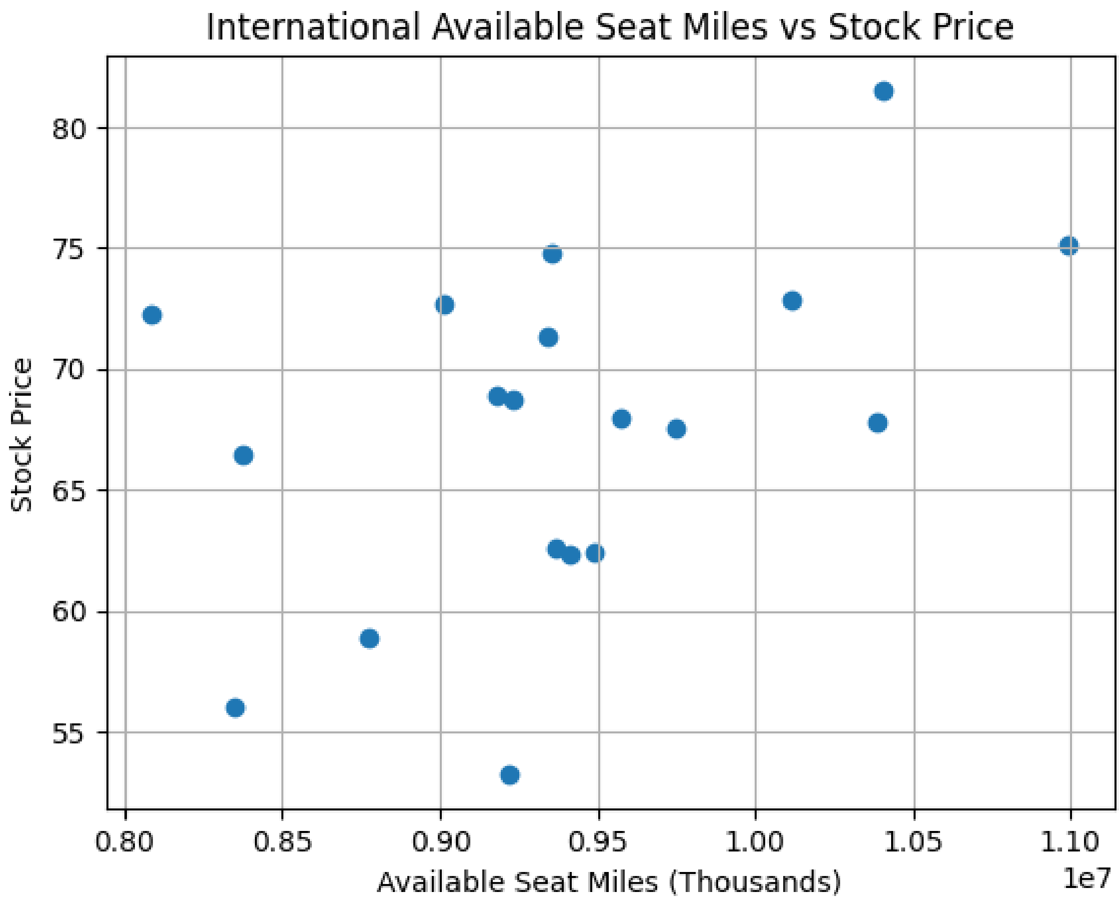

Figure 3: Correlation Coeff: 0.451

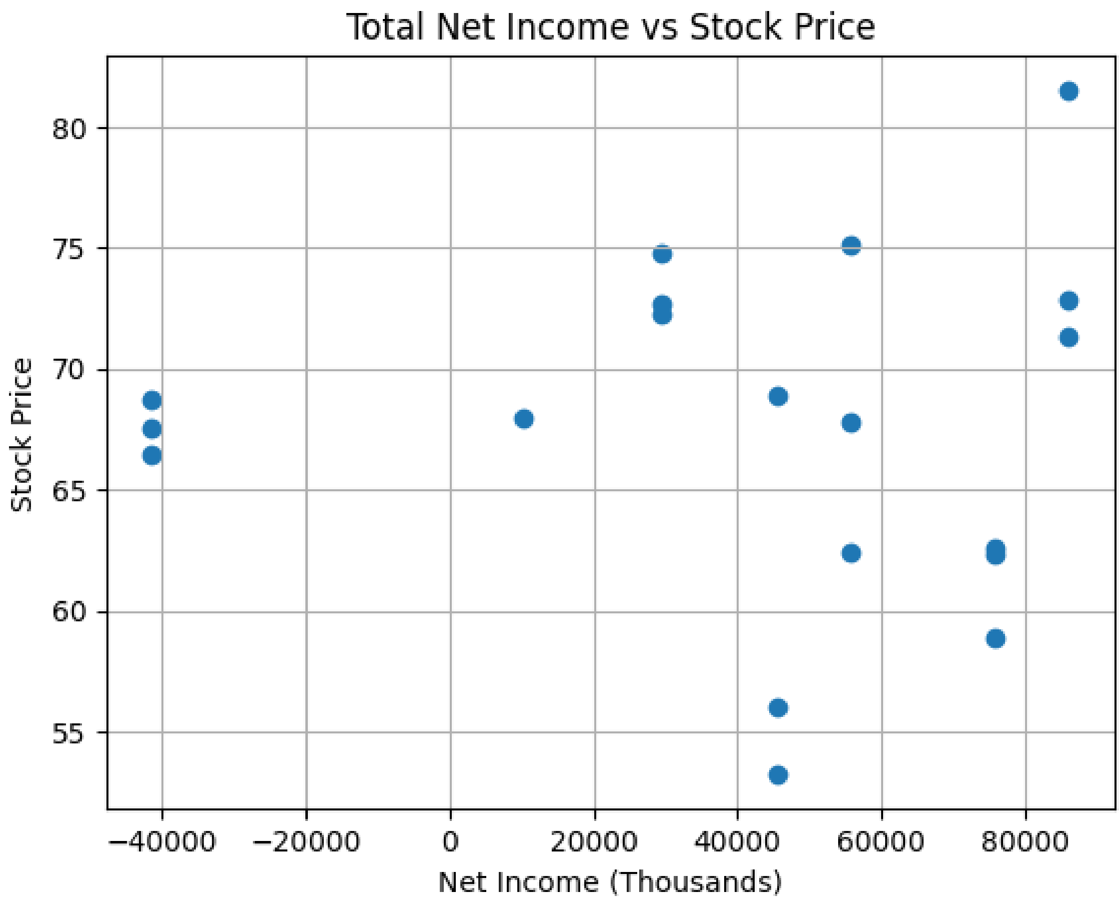

Figure 4: Correlation Coeff: 0.018

2.2 Neural Networks

In addition to examining correlations between features and stock prices, we also wanted to examine if we could use regressions to better understand stock price as a function of our features. If there was a reasonable loss function convergence of a neural network, that would mean that we could use these neural networks to predict stock prices from known statistics.

In implementing this, we used both a Convolutional Neural Network and a Recurrent Neural Network. The CNN was used as a somewhat naive approach, known to be reliable due to parameter sharing and techniques like pooling, but more suited to image processing. The RNN, however, is a model more tailored for this, using Long Short-Term Memory for time series analysis. The RNN's ability to recall historical data made it particularly useful in this task. They both had fairly involved structures, with the CNN using multiple convolutional filter layers alongside regularization and dropout, and with the RNN having many LSTM and dropout processes.

These networks were trained on the feature data from 2016-2018, trying to predict stock prices. Data was split into training and test groups. The following records the losses for the test data.

Airline	CNN Test Loss	RNN Test Loss
Alaska	279.083	277.275
American	560.736	42.308
Delta	388.968	31.741
Hawaiian	318.189	79.660
JetBlue	974.141	47.522
Southwest	6.185	10.495
Spirit	273.546	236.685
United	971.963	241.952

These values indicate that, at least for certain airlines, there is an ability to predict the stock price based on public information. With a greater span of historical data, other financial indicators (rolling average, percent change), more involved architectures, and greater computational power, we estimate that the RNN approach based on these features could serve as an important tool in market understanding.

A Appendix

A.1 Stock Price Features

As mentioned, we created various features for stock price that we did not use due to time constraints. These features were: simple moving averages (SMA) for 7, 14, 30, and 90 day windows, percent changes for the windows, and the natural logarithm of the price. SMA is a common technical indicator that helps reduce noise and provides a clearer picture of the underlying price direction. We applied the natural logarithm to the stock price to stabilize variance, as stock prices often exhibit exponential growth patterns. Percent changes express price movements as percentages, making them more interpretable and comparable across different stocks or time periods. This would put focus on the relative changes rather than the absolute values, making it easier to identify patterns and trends in the data. These features may increase model accuracy, but we encountered trouble with trying to analyze these features with the underlying data at scale in a timely matter. This was an issue given that the airline performance data was cleaned in order to align with stock price, not windows which have NaN values until the first window is complete. Future work should incorporate these features into the model.

A.2 Feature Selection Model

We created a feature selection script, located in the second cell of Datathon23Code.ipynb, that parses the outputs of relevant notebooks and returns a dataframe of features and correlations, ordered from highest correlation to lowest. Given time constraints, we were unable to use this script as an input to the RNN. Future work on this subject should use our feature selection script in order to create a RNN with the highest correlated features, as well as taking into account any strong negative correlations. This approach would improve the performance of the recurrent neural network in predicting stock price.

References

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