Impact of COVID-19 on Airline Pricing

By
Irina Zotova, Ph.D. and Pyung Yu

Micronomics
Economic Research and Consulting

April 2021

777 South Figueroa Street
Suite 4600
Los Angeles, CA 90017
www.micronomics.com

micronomics
economic research and consulting

Executive Summary

The COVID-19 pandemic produced unprecedented, unimaginable devastation throughout the world. The need to self-quarantine forced many industries, including the air travel business, to grind to a halt, producing potentially irreparable consequences. In order to better understand the extent of the impact on the airline industry, we applied sophisticated econometric techniques to voluminous flight data maintained by the United States Department of Transportation and determined that the pandemic brought about a decline in average airfares of $24 per quarter following the first quarter of 2020.

I. Introduction

In 2020, the COVID-19 virus swept across the world. As of April 2021, more than 2.9 million people died from COVID-19, with over 500,000 of those deaths occurring in the United States.[1] In an attempt to stay safe, the public was urged to adhere to precautionary guidelines involving lockdowns and social distancing.[2] This shift to self-imposed isolation significantly decreased the demand for travel.[3] See Figure 1.

[1] "Coronavirus in the U.S.: Latest Map and Case Count," The New York Times (https://www.nytimes.com/interactive/2020/us/coronavirus-us-cases.html).

"Coronavirus Global Map: Tracking the Global Outbreak," The New York Times (https://www.nytimes.com/interactive/2020/world/coronavirus-maps.html).

[2] Ewing, P., "Coronavirus Task Force Details 'Sobering' Data Behind Its Extended Guidelines," NPR website, March 31, 2020 (https://www.npr.org/2020/03/31/823916343/coronavirus-task-force-set-to-detail-the-data-that-led-to-extension-of-guideline).

Appleby, J., "Self-Quarantine? Isolation? Social Distancing? What They Mean and When to Do Them," NPR website, March 16, 2020 (https://www.npr.org/sections/health-shots/2020/03/16/816490025/quarantine-self-isolation-social-distancing-what-they-mean-and-when-to-do-them).

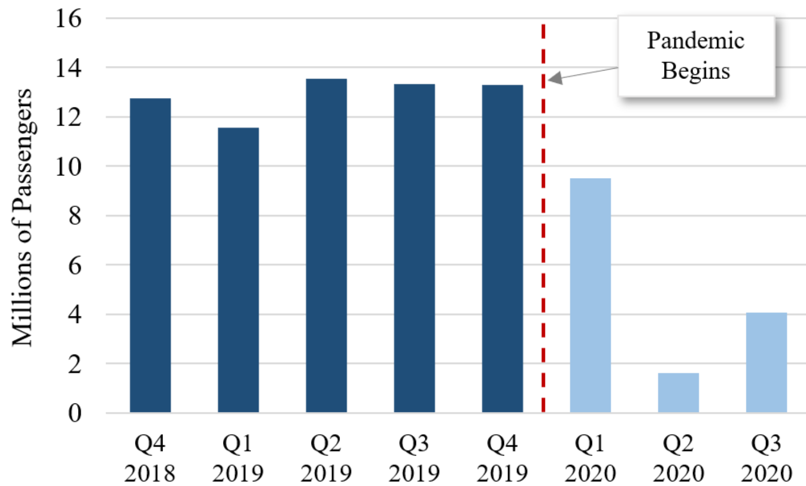
[3] Mazareanu, E., "Year-on-Year Change on Weekly Flight Frequency of Global Airlines from January 6 to January 4, 2021, By Country," Statista, January 13, 2021 (https://www.statista.com/statistics/1104036/novel-coronavirus-weekly-flights-change-airlines-region/).

Bouwer, J., Krishnan, V. and Saxon S., "Will Airline Hubs Recover from COVID-19?" McKinsey website, November 5, 2020 (https://www.mckinsey.com/industries/travel-logistics-and-infrastructure/our-insights/will-airline-hubs-recover-from-covid-19).

Figure 1: U.S. Airline Passenger Count

Based on Sample of 10 Percent of Airline Tickets from Reporting Carriers

Q4 2018 – Q3 2020[4]



In response, airlines were forced to drastically reduce the number of scheduled and available flights as they struggled to keep their businesses viable (see Figure 2).[5] In an order to reduce operational costs, "about 400,000 airline workers have been fired, furloughed or told they may lose their jobs due to [COVID-19]."[6] Millions of lives were disrupted, and repercussions of the virus continue to devastate.

---

[4] Airline Origin and Destination Survey Overview, Bureau of Transportation Statistics (https://www.transtats.bts.gov/DatabaseInfo.asp?QO_VQ=EFI&Yv0x=D).

[5] "American Airlines Announces Additional Schedule Changes in Response to Customer Demand Related to COVID-19," American Airlines Newsroom, March 14, 2020 (https://news.aa.com/news/news-details/2020/American-Airlines-Announces-Additional-Schedule-Changes-in-Response-to-Customer-Demand-Related-to-COVID-19-031420-OPS-DIS-03/default.aspx).

"March Day-by-Day: How Flight Cancellations Rose to 17%," Bureau of Transportation Statistics, May 20, 2020 (https://www.bts.gov/data-spotlight/cancellations-and-flights-day-march-2020).

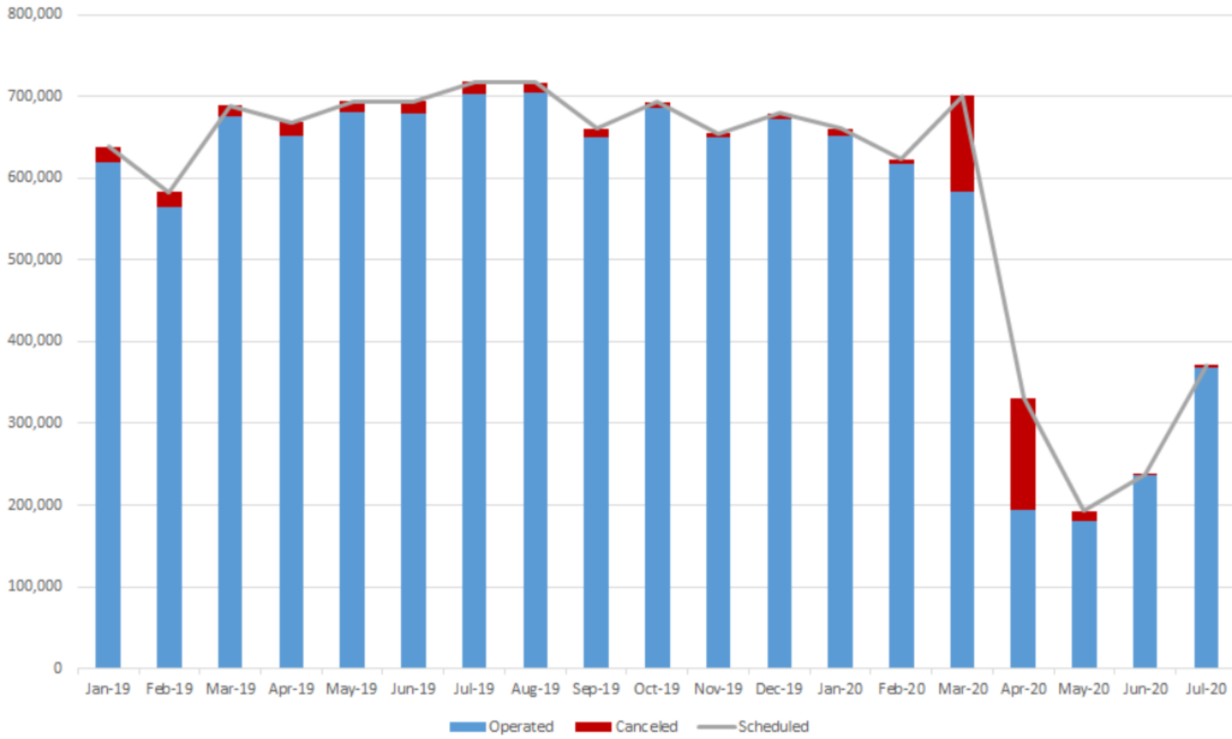
"Flight Cancellations Stabilize in May, but Total Flights Hit another Record Low," Bureau of Transportation Statistics, August 21, 2020 (https://www.bts.gov/data-spotlight/flight-cancellations-stabilize-may-total-flights-hit-another-record-low).

[6] Kelly, J., "Airlines Lost Over 400,000 Workers – United Airlines Announced Another 14,000 Jobs May Be Lost," Forbes, February 1, 2021 (https://www.forbes.com/sites/jackkelly/2021/02/01/airlines-lost-over-40000-workers-united-airlines-announced-another-14000-jobs-may-be-lost/?sh=22275e7324b3).

Popken, B. and Costello, T., "Tens of Thousands of Airline Workers are Out of Jobs After Congress Fails to Reach Deal," NBC News, September 30, 2020 (https://www.nbcnews.com/business/economy/around-35-000-people-could-lose-their-job-tonight-if-n1241588).

Figure 2: U.S. Domestic Flights Scheduled, Canceled, and Operated

January 2019 – July 2020[7]



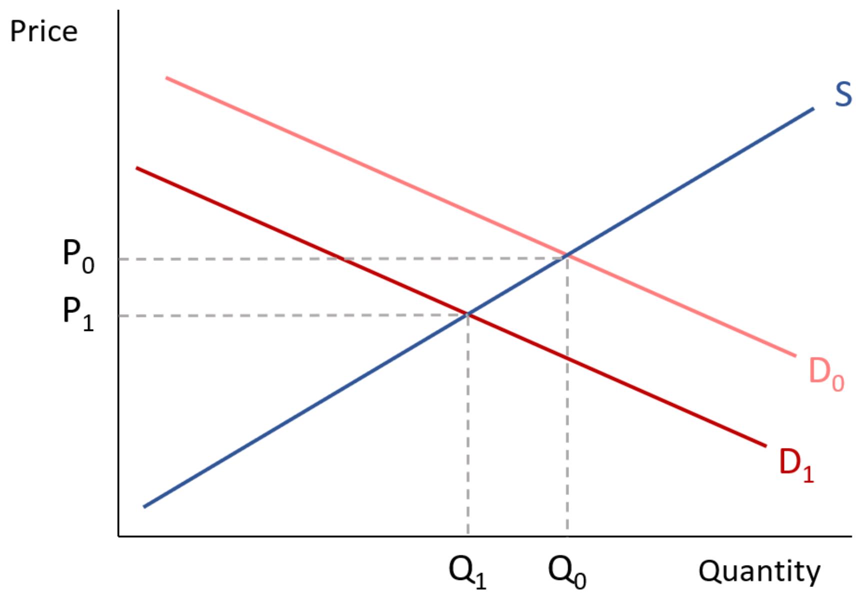
Economic theory teaches that a downward shift in demand will produce decreases in the market price and quantity of services provided. Figure 3 depicts this impact. The demand for a product or service such as air travel is represented by the line *D*. It slopes downward because other things equal, as the price of air travel declines, the volume of air travel will increase. Similarly, the availability of air travel provided by airlines (the line *S*) slopes upward, reflecting the fact that other things equal, more flights will be available at higher prices. In equilibrium, prices are set where the demand and supply curves intersect such that the supply of available seats equals total demand from passengers.

[7] Operated flights are scheduled minus canceled flights.

"U.S. Airlines operate 56% more flights in July than June," Bureau of Transportation Statistics, October 23, 2020 (https://www.bts.gov/data-spotlight/airlines-july-operations).

The pandemic, and particularly advisories to remain home and avoid crowds, had the effect of significantly reducing the demand for travel at all prices, i.e. it shifted the demand curve downward and to the left from D_0 to D_1. This change in demand produced a new equilibrium at lower price P_1 and quantity Q_1.

Figure 3: Impact of a Reduction in Demand on Price



The remainder of this paper describes use of econometric techniques to test the extent to which the law of supply and demand pertains to the airline sector by determining whether there was a statistically significant decrease in airline fares due to COVID-19, and if so, measuring the extent to which airfares declined.

II. Data

The data used for purposes of our investigation were collected from the Airline Origin and Destination Survey (the DB1B database), a 10 percent quarterly sample of all domestic airline tickets. The database was provided by the Bureau of Transportation Statistics of the U.S.

Department of Transportation, and has been maintained for more than two decades.[8] The DB1B database provides itinerary information such as the distance, fare, number of passengers, and origin and destination airports of flights, aggregated to the quarterly level.[9] A full list of variables is supplied in the Appendix.

The sample used in our analysis includes 8 quarters: the fourth quarter of 2018 through the third quarter of 2020. This time period was chosen to capture sales before and during the spread of the virus. The data were filtered such that abnormally low or high fares were excluded (less than $50 or greater than $2,000), as were itineraries with more than 4 ticket coupons (flight segments). Fares were divided to count each direction of a round-trip itinerary separately.

The data set provides the number of passengers who paid the same fare for a specific market and carrier during a given quarter. Accordingly, different fares on the same flight generate separate observations. The fares were aggregated for each origin and quarter. After aggregating and filtering for unusable data, we were left with 3,365 usable observations, each of which reflects an originating airport and associated average fare during each quarter.[10]

Figure 4 sets forth average fares of six origin airports that exhibit significant variation in the volume of passenger traffic handled.[11] The vertical red line depicts the onset of the pandemic

---

[8] Airline Origin and Destination Survey Overview, Bureau of Transportation Statistics (https://www.transtats.bts.gov/DatabaseInfo.asp?QO_VQ=EFI&Yv0x=D).

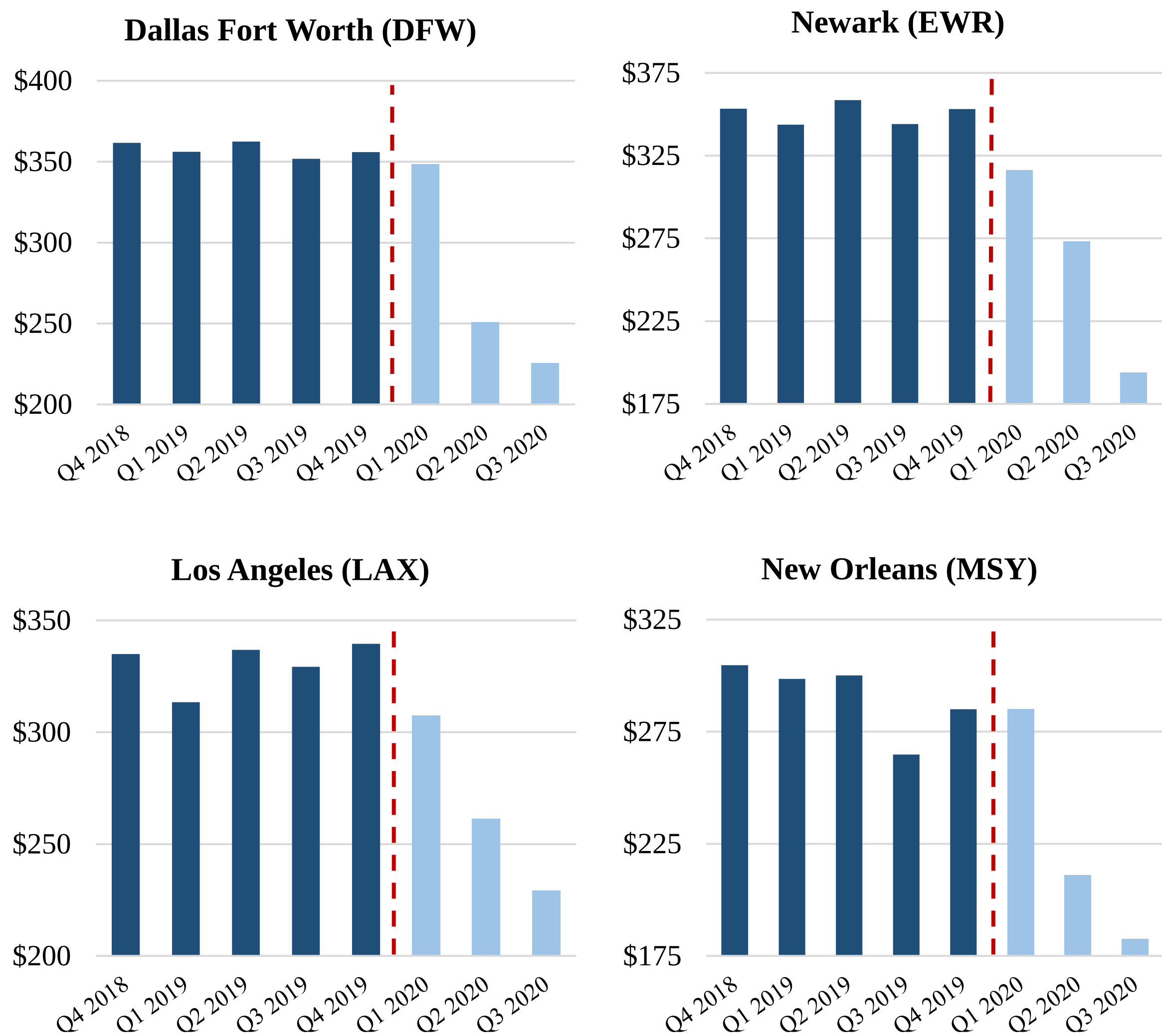
[9] "Fares are based on the total ticket value which consists of the price charged by the airlines plus any additional taxes and fees levied by an outside entity at the time of purchase. Fares include only the price paid at the time of the ticket purchase and do not include other fees, such as baggage fees, paid at the airport or onboard the aircraft." *See*: "Average Domestic Airline Itinerary Fares," Bureau of Transportation Statistics (https://www.transtats.bts.gov/AverageFare/).

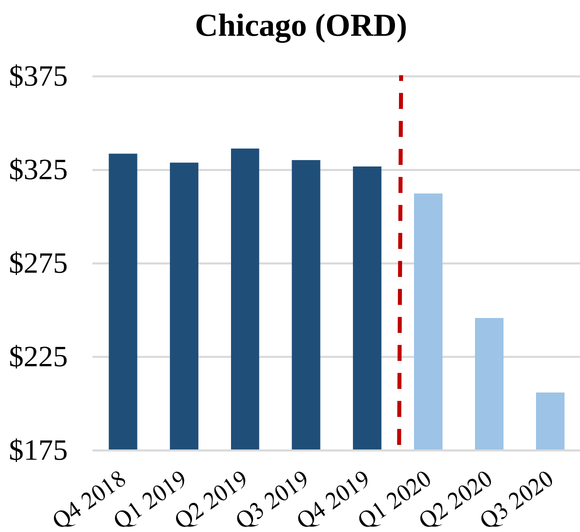
[10] The original dataset contained 68,263,384 observations.

[11] Los Angeles, Chicago O'Hare, Dallas/Fort Worth, San Francisco, Newark, and New Orleans are ranked as numbers 2, 3, 4, 7, 12, and 38 busiest U.S. airports, respectively. *See*: Deane, S., "200 Busiest U.S. Airports List," Stratos Jet Charters website (https://www.stratosjets.com/blog/busiest-us-airports/).

at the beginning of 2020. Based on information set forth in Figure 4, it is apparent that fares in 2020 were significantly lower than in 2019.

Figure 4: Average Fares per Quarter
For Six Major U.S. Airports
Q4 2018 – Q3 2020





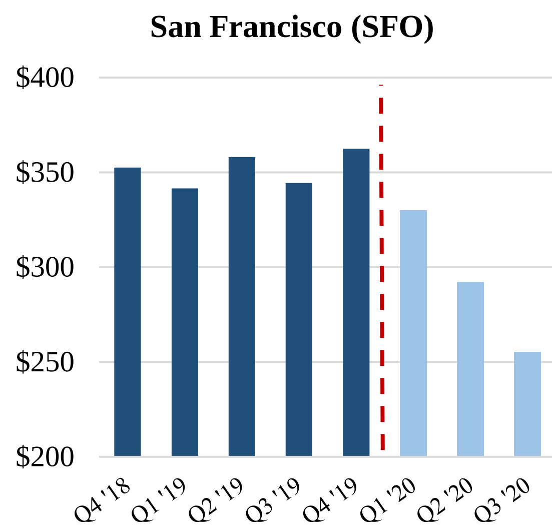


Table 1 displays average fares weighted by passenger count. These figures reflect data aggregated to the origin-quarter level.[12] Average fares decreased from $218 in the fourth quarter of 2018 to $157 in the third quarter of 2020, supporting the observations in the preceding graphs.

Table 1: Summary Statistics of Average Fare per Quarter

Quarter	Mean
2018 Q4	$218
2019 Q1	214
2019 Q2	221
2019 Q3	215
2019 Q4	216
2020 Q1	206
2020 Q2	177
2020 Q3	157

III. Model

Several statistical tests were implemented to analyze the effect of the pandemic on airline fares. First, the Gregory-Hansen test for cointegration was used to establish if and when fares

[12] In other words, data are combined to create one observation per each origin airport every quarter.

experienced a shift. Next, a time series regression was built to quantify the trend in fares before and during the determined shift.

Cointegration is a technique used to check for correlation between multiple time series.[13] Variables that move together with time are considered to be cointegrated.[14] However, a shift in a variable's path suggests a "structural break" in the data.[15] This phenomenon, and its timing, can be verified by the Gregory-Hansen test for cointegration.[16]

Gregory-Hansen tests a null hypothesis of no cointegration (i.e. no correlation between two variables) against the alternate hypothesis of cointegration with a structural break.[17] The null hypothesis is rejected if panel data experiences an abrupt change at a specific point in time. Furthermore, the alternate hypothesis implies that two variables move in the same direction with similar growth rates in the long run, as long as a structural break is incorporated.[18]

Assuming the Gregory-Hansen test confirms a structural break, an interrupted time series (ITS) regression can determine the impact of the pandemic on airline fares. A time series regression is a tool used by economists to measure the influence of one or more independent variables on a dependent variable over time.

---

[13] A time series is a sequence of data points recorded at regular time intervals. *See*: "What is Time Series?" Investopedia website (https://www.investopedia.com/terms/t/timeseries.asp).

Gonzalo, J., "Cointegration and Error Correlation," Universidad Carlos III de Madrid website (http://www.eco.uc3m.es/~jgonzalo/teaching/EconometriaII/cointegration.HTM).

[14] Gonzalo, J., "Cointegration and Error Correlation," Universidad Carlos III de Madrid website (http://www.eco.uc3m.es/~jgonzalo/teaching/EconometriaII/cointegration.HTM).

[15] "A structural break occurs when we see a sudden change in a time series or a relationship between two time series." *See*: Hyndman, R., "Structural Breaks" (https://robjhyndman.com/hyndsight/structural-breaks/).

[16] Gregory, A.; Hansen, B. (1996), "Tests for Cointegration in Models with Regime and Trend Shifts," *Oxford Bulletin of Economics and Statistics*. 58 (3): 555–560.

[17] A null hypothesis states there is no statistically significant relation between two events or populations.

[18] Gregory, A.; Hansen, B. (1996), "Tests for Cointegration in Models with Regime and Trend Shifts," *Oxford Bulletin of Economics and Statistics*. 58 (3): 555–560.

An interrupted time series design evaluates "the effectiveness of population-level [] interventions that have been implemented at a clearly defined point in time."[19] The intervention in this study is the outbreak of the virus followed by the self-imposed and government-mandated orders to stay at home.[20] The model takes on the following form:

$$Y_t = \beta_0 + \beta_1 T + \beta_2 X_t + \beta_3 T X_t$$

Y_t is the dependent variable and the fares at time t. T is an independent variable equal to the amount of time that has elapsed since the beginning of the study. X is a binary dependent variable that takes on a value of 1 for observations that are post-intervention and 0 otherwise.

The ITS regression estimates each of the β coefficients and indicates their statistical significance. β_0 is the baseline level of the dependent variable at $T = 0$. β_1 is the change in the dependent variable with a time unit increase (representing the pre-intervention trend). β_2 is the change in level following the intervention and β_3 is the change in slope post-intervention.[21] Each coefficient represents the difference in the predicted value of fares, given that the other independent variables remain constant.

---

[19] Bernal, J.L., Cummins, S., and Gasparrini, A., "Interrupted Time Series Regression for the Evaluation of Public Health Interventions: A Tutorial," *Int J Epidemiol*. 2017; 46(1):299-309.

[20] "A Timeline of COVID-19 Developments in 2020," American Journal of Managed Care (https://www.ajmc.com/view/a-timeline-of-covid19-developments-in-2020).

Wu. J., Smith S., Khurana M., Siemaszko C., and DeJesus-Banos B., "Stay-at-Home Orders Across the Country," NBC News, March 25, 2020 (https://www.nbcnews.com/health/health-news/here-are-stay-home-orders-across-country-n1168736).

[21] Bernal J.L., Cummins S., and Gasparrini A., "Interrupted Time Series Regression for the Evaluation of Public Health Interventions: A Tutorial," *Int J Epidemiol*. 2017; 46(1):299-309.

IV. Results

The Gregory-Hansen test rejected the null hypothesis of no cointegration by establishing a level shift at the first quarter of 2020.[22] The Augmented Dickey Fuller test and Z_t statistic were found to be significant at least at the 5 percent level, as shown in Table 2.[23]

Table 2: Gregory-Hansen Test for Cointegration

ADF	Break Date	Z_t	Break Date	Z_α	Break Date
-4.80**	2020 Q1	-5.22***	2020 Q1	-14.39	2020 Q1

The 5% critical values for ADF, Z_t, and Z_α are -4.61, -4.61, and -40.48, respectively.

** indicates significance at 5%.

*** indicates significance at 1%.

Following this result, an ITS regression was performed by specifying an intervention at the first quarter of 2020. Figure 5 depicts quarterly average fares of flights departing the top twenty busiest U.S. airports.[24] The generated regression result is overlayed on the scatter plot, with the vertical red line establishing the start of the pandemic.

[22] To run the test, data was aggregated to create one point per quarter, which was the average of the fares for each quarter weighted by the passenger count.

[23] The ADF test and z-test are used to establish stationarity between two samples.

A z-test is used to determine whether two population means are different. A z-scores is "a number representing how many standard deviations above or below the mean population a score derived from a z-test is." *See*: "Z-Test," Investopedia website (https://www.investopedia.com/terms/z/z-test.asp).

The Augmented Dickey-Fuller test is a unit root test for stationarity. "A time series has stationarity if a shift in time doesn't cause a change in the shape of the distribution; unit roots are one cause for non-stationarity." *See*: "What is 'Unit Root'?" Statistics How To website (https://www.statisticshowto.com/unit-root/).

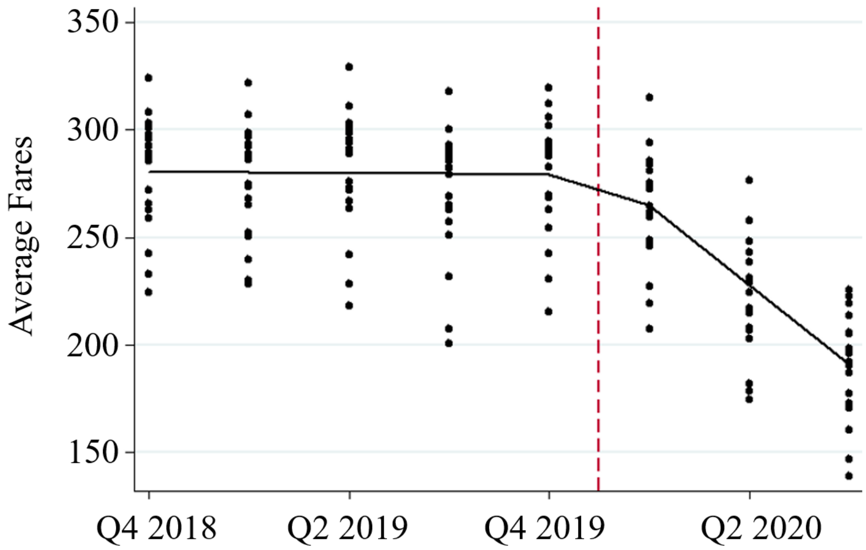
The significance level is "the probability of rejecting the null hypothesis when it is true. For example, a significance level of 0.05 indicates a 5% risk of concluding that a difference exists when there is no actual difference." *See*: "Understanding Hypothesis Tests: Significance Levels (Alpha) and P Values in Statistics," Minilab website (https://blog.minitab.com/en/adventures-in-statistics-2/understanding-hypothesis-tests-significance-levels-alpha-and-p-values-in-statistics).

[24] The top 20 busiest U.S. airports in 2019 were ranked by the Bureau of Transportation Statistics. *See*: "Average Domestic Airline Itinerary Fares," Bureau of Transportation Statistics (https://www.transtats.bts.gov/AverageFare/).

Figure 5: Average Fares per Quarter

Top 20 Busiest U.S. Airports

Q4 2018 – Q3 2020



Regression results are set forth in Table 3. The adjusted R^2 for the regressions that include all origin airports provided by the Bureau of Transportation Statistics and a subset of the data consisting of the top 20 busiest U.S. airports are 0.176 and 0.390, respectively.[25]

[25] R^2 is a measure of the goodness of fit of the regression. It tells how much of the variation in the dependent variable is explained by the regression on the independent variables. R^2 ranges in values from 0 to 1; 0 indicates the independent variables explain no variation in the dependent variable and 1indicated the independent variables explain all the variation in the dependent variable. In the present analysis, an R^2 of 0.176 means 17.6 percent of the variation in airline ticket prices is explained by the independent variables used in the regression. *See*: King, Anna C., Rao, Mohan P., and Tregillis, Christian D., "Econometric Analysis," *Litigation Services Handbook, Sixth Edition*, 2017, p.24; Hill, R. Carter, Griffiths, William E., and Lim, Guay C., *Principles of Econometrics, Third Edition*, 2008, pp. 80-81; and Pindyck, Robert S. and Rubinfeld, Daniel L., *Econometric Models and Economic Forecasts, Fourth Edition*, 1998, p. 72.

Table 3: Regression Results

	All Airports n = 3,365			Top 20 Domestic Airports by Population n = 160		
	Coefficient	P-Value	95% CI	Coefficient	P-Value	95% CI
Pre-COVID-19 Intercept	217.29	0.000	214.57; 220.02	280.76	0.000	270.10; 291.43
Pre-COVID-19 Slope	-0.19	0.640	-1.01; 0.619	-0.28	0.860	-3.46; 2.89
COVID-19 Intercept Change	13.26	0.000	7.86; 18.66	22.30	0.039	1.15; 43.45
COVID-19 Slope Change	-24.19	0.000	-27.01; -21.36	-36.55	0.000	-47.53; -25;57

The pre-COVID-19 intercept is $217.29. Before the pandemic, airline ticket prices experienced an average decrease of $0.19 per quarter. This means average fares were held constant at approximately $217.

The regression results show that since the start of the pandemic, airline prices have experienced an upward shift in the intercept of $13.26 along with a decrease of an average of $24.19 per quarter.[26] This means that in the first quarter of 2020, the net decrease in average airfares was $10.93 when compared to the last time period before the pandemic, the fourth quarter of 2019.[27] From this point forward, fares decreased by an average of $24.19 each subsequent quarter.

The sample data restricted to the top 20 busiest airports produced similar results. The pre-COVID-19 intercept is $280.76. Before the pandemic, airline ticket prices experienced a statistically insignificant average decrease of $0.28 per quarter. This means average fares were held constant at approximately $280.

The regression results show that since the start of the pandemic, airfares associated with flights leaving the 20 busiest airports have experienced an upward shift in the intercept of $22.30

[26] The changes in intercept and slope are both statistically significant.
[27] $10.93 = $24.19 - $13.26

along with a decrease of an average of $36.55 per quarter.[28] This means that in the first quarter of 2020, the net decrease in average airfares was $14.25 when compared to the last time period before the pandemic, the fourth quarter of 2019.[29] From this point forward, fares decreased by an average of $36.55 each quarter.

One of the necessary assumptions in a linear regression model is that observations are independent. This assumption is violated when consecutive observations are similar, a problem that is referred to as autocorrelation.[30] To verify the validity of the time series model, a LOWESS (Locally Weighted Scatterplot Smoothing) curve can be built from the residuals of a regression.[31] LOWESS "is a method of regression analysis which creates a smooth line through a scatterplot [that] provides a means to figure out relationships between variables" and helps locate a trend, if one exists.[32]

Figure 6 sets forth graphs of regression residuals plotted against time. The horizontal LOWESS curves signify a lack of correlation between residuals in the regressions, thus verifying the legitimacy of the existing models.

---

[28] The changes in intercept and slope are both statistically significant.

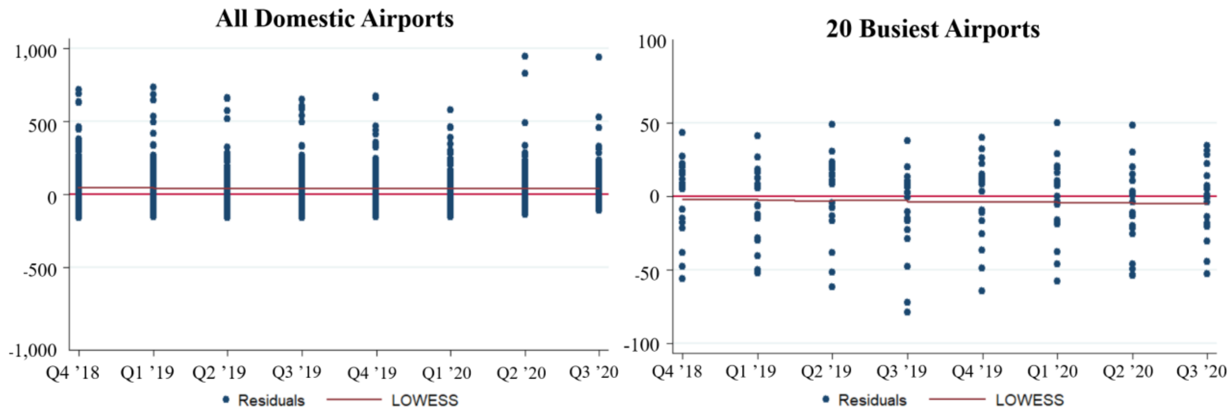
[29] $14.25 = $36.55 - $ 22.30

[30] Bernal J.L., Cummins S., and Gasparrini A., "Interrupted Time Series Regression for the Evaluation of Public Health Interventions: A Tutorial," *Int J Epidemiol*. 2017; 46(1):299-309.

[31] A residual is defined as the observed value of Y_i minus the fitted value generated by the regression. *See:* "Common Mistakes in Using Statistics: Spotting and Avoiding Them," Department of Mathematics, The University of Texas at Austin (https://web.ma.utexas.edu/users/mks/statmistakes/modelcheckingplots.html).

[32] Erkec, E., "Locally Weighted Scatterplot Smoothing (Lowess) Approach in Power BI," MS SQL Tips website, August 14, 2018 (https://www.mssqltips.com/sqlservertip/5600/locally-weighted-scatterplot-smoothing-lowess-approach-in-power-bi/).

Figure 6: Regression Residuals



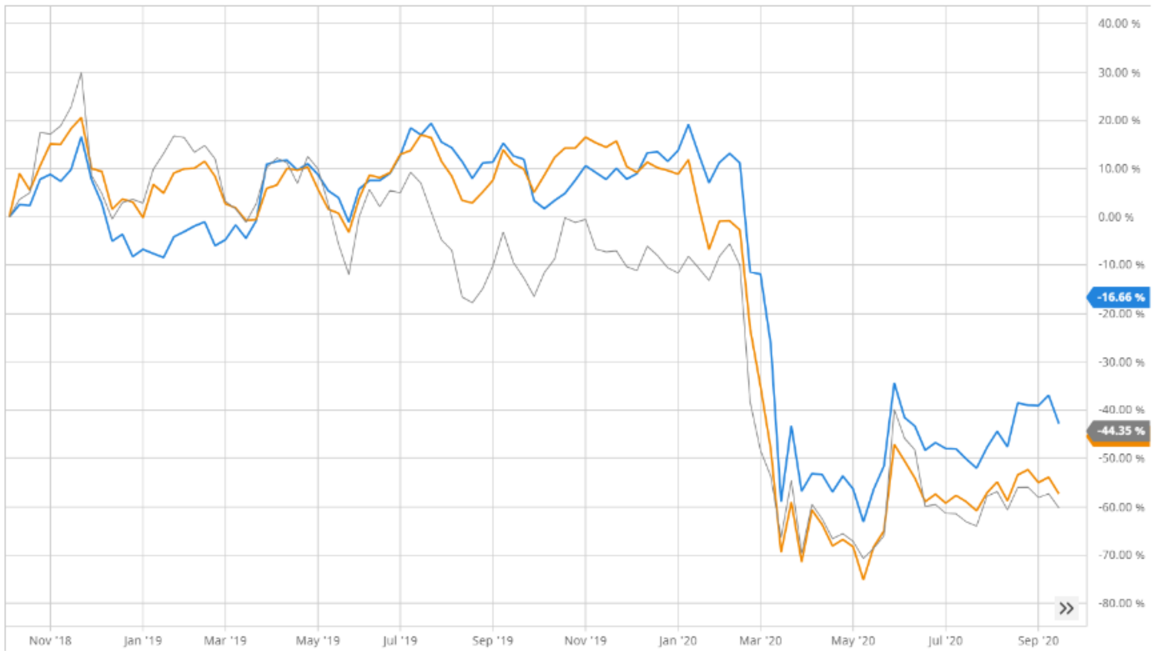
To summarize briefly: the shift in demand brought on by the pandemic produced a reduction in airfares of $24 per quarter. The stock market recognized the oncoming disaster, with stock prices and airline valuations abruptly crashing. Following the prolonged restrictions on air travel and decrease in demand for flights, airline stock prices have remained low, as seen in Figure 7.[33] Legacy carriers lost over half of their stock value in 2020. Accordingly, the decrease in fares and passenger count directly influenced airline profits and stock value.

[33] Maneenop S., Kotcharin S., "The Impacts of COVID-19 on the Global Airline Industry: An Event Study Approach," *Journal of Air Transport Management*, Volume 89, 2020, 101920.

Figure 7: Percentage Change in Stock Prices Relative to October 2018

American Airlines, Delta Airlines, United Airlines

October 2018 – September 2020[34]



Grey: American Airlines; **Blue: Delta Airlines**; **Orange: United Airlines**

V. Conclusion

This study evaluates the effect of COVID-19 on domestic U.S. airfares since the pandemic began in the first quarter of 2020. An Interrupted Time Series regression shows that there was a statistically significant reduction in fares in 2020 compared to the previous, pre-pandemic year, of $24 per each additional quarter. Given that the pandemic is ongoing, it is unknown how long its influence on prices will last. In all likelihood, the ripple effect of the COVID-19 pandemic will be more prolonged than any other airline adverse events affecting the industry.[35]

[34] Bar Chart website (https://www.barchart.com/stocks/quotes/AAL/interactive-chart).

[35] Research has found that an airline crash reduces airfares of the crash airline "only in the months right after the crash, indicating that the financial ramifications are not persistent." *See*: Zotova, I., 2017 "Post-Crash Airline Pricing: A Case Study of Alaska Airlines Flight 261," *Economics of Transportation* 10, 18-22.

Indeed, it is possible that demand for air travel will never fully recuperate to pre-pandemic levels. Companies have adjusted to the pandemic by allowing employees to work from home, and after experiencing the benefits of remote work, many are considering the possibility of not returning to offices in the long term.[36] This change could permanently decrease demand for business travel. According to the Environmental Systems Research Institute, recent analysis "predicts that business travel could be down more than a third even after the COVID-19 pandemic recedes."[37] The pandemic has given the public an opportunity to reevaluate their needs and jolted the economy in a different direction.

---

[36] Snouwaert, J., "54% of Adults Want to Work Remotely Most of the Time After the Pandemic, According to a New Study From IBM," Business Insider website, May 5, 2020 (https://www.businessinsider.com/54-percent-adults-want-mainly-work-remote-after-pandemic-study-2020-5).

Hadden, J., Sonnemaker, T., and Borden, T., "21 Major Companies That Have Announced Employees Can Work Remotely Long-Term," Business Insider website, December 14, 2020 (https://www.businessinsider.com/companies-asking-employees-to-work-from-home-due-to-coronavirus-2020).

[37] Sankary, G., "Massive Drop in Business Travel Could be Permanent," Environmental Systems Research Institute website, December 21, 2020 (https://www.esri.com/about/newsroom/publications/wherenext/business-travel-decline/).

Appendix

Origin and Destination Survey

Field Name	Description
ItinID	Itinerary ID
MktID	Market ID
SeqNum	Coupon Sequence Number
Coupons	Number of Coupons in the Itinerary
Year	Year
OriginAirportID	Origin Airport, Airport ID. An identification number assigned by US DOT to identify a unique airport. Use this field for airport analysis across a range of years because an airport can change its airport code and airport codes can be reused.
OriginAirportSeqID	Origin Airport, Airport Sequence ID. An identification number assigned by US DOT to identify a unique airport at a given point of time. Airport attributes, such as airport name or coordinates, may change over time.
OriginCityMarketID	Origin Airport, City Market ID. City Market ID is an identification number assigned by US DOT to identify a city market. Use this field to consolidate airports serving the same city market.
Quarter	Quarter (1-4)
Origin	Origin Airport Code
OriginCountry	Origin Airport, Country Code
OriginStateFips	Origin Airport, State FIPS Code
OriginState	Origin Airport, State Code
OriginStateName	Origin State Name
OriginWac	Origin Airport, World Area Code
DestAirportID	Destination Airport, Airport ID. An identification number assigned by US DOT to identify a unique airport. Use this field for airport analysis across a range of years because an airport can change its airport code and airport codes can be reused.
DestAirportSeqID	Destination Airport, Airport Sequence ID. An identification number assigned by US DOT to identify a unique airport at a given point of time. Airport attributes, such as airport name or coordinates, may change over time.
DestCityMarketID	Destination Airport, City Market ID. City Market ID is an identification number assigned by US DOT to identify a city market. Use this field to consolidate airports serving the same city market.
Dest	Destination Airport Code

DestCountry	Destination Airport, Country Code
DestStateFips	Destination Airport, State FIPS Code
DestState	Destination Airport, State Code
DestStateName	Destination State Name
DestWac	Destination Airport, World Area Code
Break	Trip Break Code
CouponType	Coupon Type Code
TkCarrier	Ticketing Carrier Code
OpCarrier	Operating Carrier Code
RPCarrier	Reporting Carrier Code
Passengers	Number of Passengers
FareClass	Fare Class Code. Value Is Defined By Carriers And May Not Follow The Same Standard. Not Recommended For Analysis.
Distance	Coupon Distance
DistanceGroup	Distance Group, in 500 Mile Intervals
Gateway	Gateway Indicator (1=Yes)
ItinGeoType	Itinerary Geography Type
CouponGeoType	Coupon Geography Type
OriginCountry	Origin Airport, Country
OriginStateFips	Origin Airport, State FIPS
OriginState	Origin Airport, State
RoundTrip	Round Trip Indicator (1=Yes)
OnLine	Single Carrier Indicator (1=Yes)
DollarCred	Dollar Credibility Indicator
FarePerMile	Itinerary Fare Per Miles Flown in Dollars (ItinFare/MilesFlown).
RPCarrier	Reporting Carrier
ItinFare	Itinerary Fare Per Person
BulkFare	Bulk Fare Indicator (1=Yes)
Distance	Itinerary Distance (Including Ground Transport)
MilesFlown	Itinerary Miles Flown (Track Miles)

About the Authors

Irina Zotova is an economist and Consultant at Micronomics, an economic research and consulting firm based in Los Angeles, California. At Micronomics, Dr. Zotova has been engaged with matters involving the airline industry, patent infringement, insurance, and fraud. Her consulting experience includes extensive use of econometric techniques, regression analysis, and calculation of lost profits and reasonable royalties. Dr. Zotova's dissertation included topics in transportation and experimental economics. Her research on the impact of the crash of Alaska Airlines Flight 261 on fares of the crash carrier was published in the journal Economics of Transportation. She has also worked as a Graduate Teaching Assistant for economics courses. Dr. Zotova received a Ph.D. and M.A. in Economics from the University of California, Irvine and a B.S. in Mathematics and Economics from the University of California, San Diego.

Pyung Yu is a Research Associate at Micronomics. He has extensive consulting experience with respect to the calculation of reasonable royalties and lost profits in connection with intellectual property infringement litigation. He has also valued patents in the context of negotiating licenses and arbitrations, as well as conducted relevant market studies. Industries studied include semiconductors, banking, telecommunications, and software. Mr. Yu received a B.A. in Economics from the University of Pennsylvania.

About Micronomics

Micronomics is an economic research and consulting firm with offices in Los Angeles and Long Beach, California. Founded in 1988, it specializes in the collection, tabulation and analysis of various types of economic, financial and statistical data. Areas of expertise include industrial organization, antitrust, economic impact studies, the valuation of intellectual property and the calculation of economic damages. Clients include publicly and privately held businesses and government agencies. Industry experience includes sports and entertainment, banking and financial services, pharmaceuticals, telecommunications, and computer hardware and software.