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Quantifying the impact of the COVID-19 pandemic on US airline stock prices

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ABSTRACT

This paper uses data at the trading day frequency and the method of local projections to quantify the dynamic responses of U.S. airline stock prices to a COVID-19 shock. We show that airline stock prices decline immediately by 0.1 percentage point in response to a 1% COVID-19 shock. In addition, the effect of the shock persists beyond the day on which it occurs, with most airline stock prices falling by as much as 0.6 percentage points after fifteen days. This negative response of airline stock prices to a COVID-19 shock is not explained by a COVID-19-induced increase in airlines’ variable costs, but rather by a COVID-19-induced decrease in air travel, which, in turn decreases revenues, profitability, and stock prices of U.S. airlines.

1. Introduction

The 2019 Coronavirus Disease (COVID-19) has wreaked havoc on the global economy and financial markets. In the United States, the Business Cycle Dating Committee of the National Bureau of Economic Research determined that the U.S. economy entered a recession in February 2020. Aggregate U.S. output in April 2020 declined by almost 18% from its most recent one-year peak (which occurred in November 2019), while the economy lost a staggering 20.5 million jobs, causing the April unemployment rate to rise to 14.7%. On March 23, 2020, the S&P 500 had tumbled by 51% from its most recent (and record all-time) high achieved on February 19, 2020. To alleviate the economic fallout of this COVID-induced recession, the U.S. Congress passed, and President Donald Trump signed into law the Coronavirus Aid, Relief, and Economic Security (CARES) Act on March 27, 2020. On its part, the Federal Reserve cut the target federal funds rate to almost zero, has committed to purchasing at least 500 billion dollars in Treasury securities and 200 billion dollars in mortgage-backed securities, while simultaneously pursuing other aggressive actions to stabilize the U.S. Treasury market, support consumers, corporations, and state and local governments.

While the COVID-19 pandemic has had damaging consequences on the U.S. economy and financial markets, the effects on the U.S. airline industry have been even more devastating, with the industry currently experiencing its sharpest contraction since World War II (Council of Economic Advisers, 2020; Airlines for America, 2020). Data from the Transportation Security Administration (TSA), the agency responsible for security screening of passengers prior to boarding, indicate that only about 95,000 passengers were screened at the country’s airports on April 16, 2020. This represents a 96% decline from 2.6 million on the same day the year before. Fig. 1A highlights this dramatic impact of the COVID-19 pandemic on air travel as measured by passenger screenings at TSA checkpoints for the period January 1, 2020 to March 15, 2021. Fig. 1B further shows that U.S. carriers operated significantly fewer flights since the outbreak of the pandemic, however, the slope is...
of protective measures, air travel demand remains low. This decrease in U.S. domestic (and international) air travel, coupled with general economic uncertainty surrounding the COVID-19 pandemic, is expected to decrease current and expected future cash flows to airline industry firms, leading to a decline in their stock prices. In fact, Fig. 2A, which displays the daily values of the New York Stock Exchange Arca Airline Index (a summary index that tracks the stock price performance of highly capitalized major U.S. airlines) since January 20, 2020, seems to support this view. On the other hand, speculative dynamics, such as fads, investor sentiment, and/or overreaction to news about the pandemic may lead to considerable volatility in airline industry stock prices, as shown in Fig. 2B. This may be seen by some investors as an opportunity for greater reward, prompting higher trading, and potentially impacting prices. Furthermore, the CARES Act, which contains provisions of up to $25 billion in grants to passenger airlines, with stipulations for an additional $25 billion in government loans in case private financing cannot be secured, may not only prevent further declines in airline stock prices in the short run, but may even boost stock prices in the long run (Fonda, 2020).

This paper conducts a detailed investigation of the impact the COVID-19 pandemic on U.S. airline industry stock prices. The Granger-precedence of the COVID-19 pandemic with respect to the economy and stock prices, as well as its indispensible importance to the airline industry, provides an excellent opportunity to evaluate the response of airline industry stock prices to a credibly exogenous shock. Specifically, the paper makes the following contributions. First, we use high frequency (daily) to quantify the impact of a shock to the COVID-19 pandemic on U.S. airline stock prices. Second, we employ the method of local projections (Jordão, 2005) to estimate impulse response functions, and show that a shock to the COVID-19 pandemic has effects on airline stock prices that persist beyond the day on which the shock occurs. Third, we provide evidence that the response of the airline stock prices depend, to some extent, on the magnitude of the COVID-19 pandemic shock. Fourth, we examine whether the stock price responses to a COVID-19 shock we observed are potentially moderated by the use of masks or vaccine administration in the later part of our sample time period. Fifth, we extrapolate the potential wealth effects associated with a COVID-19 shock in terms of loss in market capitalization. To the best of our knowledge, this study represents the first attempt to estimate the dynamic response impacts of the COVID-19 pandemic on U.S. airline stock prices.

Using stock price data on the eleven publicly traded U.S. airline firms, as well as an aggregate index that tracks the stock price performance of the major U.S. airlines, our results indicate that a shock to the COVID-19 pandemic has economically and statistically significant effects on U.S. airline stock prices. In particular, the contemporaneous response of each of the twelve stock prices is negative and significantly different from zero. Furthermore, for most of the airline stock returns, this decline is persistent, lasting well beyond two weeks after the initial COVID-19 shock. In addition, we find some evidence that the decline in stock prices is larger following a large COVID-19 shock relative to a small shock, although there is heterogeneity across airlines. We find no mask mandate moderating effects on stock price responses and argue that regional mask mandates do not add further information or impact because they mainly follow the CDC guidelines which are public knowledge to investors and are already priced in. We also find no vaccine administration moderating effects on stock price responses from a COVID-19 shock.

Our results suggest that despite airlines taking a multitude of actions to increase their cash flows and improve investor confidence, together with the federal government’s efforts to help shore up the aviation industry through the CARES Act, the decline in air travel due to the pandemic triggered a precipitous selloff of airline stocks and slashed the valuation of these carriers. In addition, that airline industry stock prices decline persistently reflects investors’ expectations that the capital-intensive nature of the industry makes it difficult for airlines to shed costs, even as revenues fall. This is consistent with complimentary evidence in Alfaro et al. (2020), who argue that because labor-intensive firms have the ability to furlough and/or lay off workers with relative ease during adverse economic times, investors expect smaller losses, and consequently higher returns relative to capital-intensive firms. Overall, we believe that our findings provide novel quantitative evidence on the transmission of the COVID-19 pandemic to U.S. airline industry stock prices.

Our paper is related to the small but rapidly growing literature on the economic and financial market impacts of the COVID-19 pandemic. Examples include Lewis, Mertens and Stock (2020), Baker et al. (2020), Carvalho et al. (2020), Bartik et al. (2020), Landler and Thesmar (2020), Alfaro et al. (2020), Ramelli and Wagner (2020) and Albuquerque et al. (2020). Methodologically, our paper is related to the fairly well established literature that uses local projection methods to estimate the economic and financial market responses to economic shocks (see for example, Auerbach and Gorodnichenko (2012), Owyang et al. (2013), Ramey and Zubairy (2018), Zidar (2019), Coibion et al. (2017), Alpanda and Zubairy (2019) and Atems and Sardar (2021)). There is also substantial literature that employs high frequency data to identify the effects of economic and other shocks. Recent papers in this strand of the literature include Bekaert, Hoerova and Duca (2013), Auerbach and Gorodnichenko (2016), Levin et al. (2017) and Nakamura and Steinsson (2018).

The paper is organized as follows. Section 2 presents the data and empirical methodology employed in this paper. Section 3 discusses the empirical results. Section 4 concludes.

2. Data and econometric methodology

2.1. Data

All the data used in this paper are daily data from January 21, 2020 to March 15, 2021, giving a sample of 287 observations for each variable. We start in January 21, 2020 as the first confirmed U.S. COVID-19 case was recorded on that date. All variables in the paper are expressed in their respective daily percentage changes to address concerns about potential nonstationarity. This transformation is supported by standard unit root and stationarity tests, results of which are available upon request.

The data on COVID-19 cases come from the U.S. Centers for Disease Control and Prevention (CDC). The numbers are the total confirmed and probable counts reported to the CDC by U.S. state and local jurisdictions from the previous day. The CDC excludes individuals repatriated to the U.S. from Wuhan, China, and Japan. The CDC estimates differ from those reported by other sources because the “CDC’s overall case numbers are validated through a confirmation process with each jurisdiction” (CDC, https://www.cdc.gov/covid-data-tracker/).

6 As examples of protective measures, United Airlines launched a new program, United CleanPlus, in collaboration with Clorox and Cleveland Clinic. The carrier also provides kits with masks and hand sanitizer wipes (see https://hub.united.com/2020-05-20-united-airlines-launches-united-cleanplus-a-new-standard-of-cleanliness-and-safety-in-partnership-with-clorox-and-cleveland-clinic-2646040601.html). As of April 10, 2020, Delta Airlines has adjusted its boarding process to a back-to-front scheme to enforce social distancing, among other measures (see https://news.delta.com/focused-safety-delta-moves-quickly-meet-customer-needs-during-coronavirus). American Airlines and JetBlue are imposing the strict harboring of face coverings (see https://www.aa.com/i18n/travel-info/coronavirus-updates.jsp for details).

7 Weekends, and non-trading days are omitted.
Data on stock prices for individual airlines in our data sample are collected from Yahoo Finance. To measure aggregate airline stock price performance, we use the New York Stock Exchange NYSE Arca Airline Index (XAL), a weighted index designed to track the price performance of major U.S. airlines that are highly capitalized. We also study the stock price performance of the eleven U.S. airlines traded on U.S. stock exchanges. Hence, we collect stock price data (ticker in parentheses) on Alaska Air Group, Inc. (ALK); Allegiant Travel Company (ALGT); American Airlines Group, Inc. (AAL); Delta Air Lines, Inc. (DAL); Hawaiian Holdings, Inc. (HA); JetBlue Airways Corporation (JBLU); Mesa Air Group, Inc. (MESA); SkyWest, Inc. (SKYW); Southwest Airlines Company (LUV); Spirit Airlines, Inc. (SAVE); and United Airlines Holdings, Inc. (UAL).

Since jet fuel accounts for the largest cost share for airlines, we control for the impact that jet fuel prices may have on airline stock prices. We use daily U.S. Gulf Coast Kerosene-Type Jet Fuel Prices, collected from the Federal Reserve Economic Database (FRED) of the Federal Reserve Bank of St. Louis.

2.2. Econometric methodology

2.2.1. Local projections

Empirically, we employ Jordà (2005)’s method of local projections to estimate the impulse response functions of U.S. airline industry stock prices and other variables of interest to a COVID-19 shock. As pointed out by, among others, Jordà (2005), and Stock and Watson (2007), estimating impulse response functions using local projections is an attractive alternative to vector autoregressions (VAR) because the method (i) does not impose the type of dynamic restrictions typical of VAR models (ii) is less sensitive to model misspecification (iii) can be estimated by single-equation estimation approaches, and (iv) offers a convenient way to easily account for state dependence in the impulse response functions.

In our benchmark linear specification, we generate impulse responses of airline stock prices to a COVID-19 shock by estimating a sequence of regressions at different horizons, \( h \), using the model:

\[
y_{t+h} = d^t + \sum_{i=1}^{k} \beta_i \gamma_{t-i} + \epsilon_{t+h}, \quad h = 0, 1, 2, \ldots, H - 1
\]

where \( y_t = [c_t \quad j_t \quad s_t] \) represents a three-dimensional vector of model variables. In this vector, \( c_t \) is the percentage in the number of confirmed COVID-19 cases in the U.S., \( j_t \) is the percentage change in jet fuel prices, and \( s_t \) is the percentage change in the U.S. airline industry stock price of interest. The lag length, denoted \( k \), is determined by minimizing the Schwartz Information Criterion (SIC), which consistently chooses a lag length of one. In Equation (1), \( d^t \) denotes the vector of constants, \( \beta_i \) is the matrix of parameters for a given forecast horizon \( h \), and \( \epsilon_{t+h} \) is the vector of serially correlated and/or heteroskedastic errors.

From the model (1), structural impulse response functions can be derived as:

\[
\text{IRF}(t, h, d_t) = \hat{\beta}_h d_t
\]

where \( \hat{\beta}_h = I \), and \( d_t = B_0^{-1} \) is the shock matrix relates the structural shocks to the reduced-form residuals of each element of \( y_t \). Following Jordà (2005), \( d_t \) is constructed by estimating a linear VAR model in which identification is achieved by applying the Cholesky decomposition to the variance-covariance matrix of reduced-form residuals. The ordering of the variables in \( y_t \) follows standard practice of ordering the more exogenous variables ahead of the less exogenous ones. Hence in \( y_t \), we order (the percentage change in) the number of daily COVID-19 cases ahead of jet fuel prices and airline stock prices. Consistent with the literature on the impact of energy prices on stock prices (see e.g., Kilian and Park (2009)), we impose the restriction that jet fuel prices affect but are unaffected by airline stock prices contemporaneously. Jet fuel is a byproduct of oil, and since oil prices are determined by demand and supply forces in the global crude oil market, the assumption that jet fuel prices do not respond on impact to airline stock price movements is reasonable.\(^8\)

Confidence intervals for the impulse response functions are constructed using the estimated standard errors. However, because the local projections methodology involves successive leads of the dependent variable, the estimated standard errors tend to suffer from serial correlation and/or heteroskedasticity. Thus, we apply the Newey-West

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\(^8\) Our results are not sensitive to this restriction.
correction to obtain heteroskedasticity and autocorrelation (HAC) robust standard errors, as recommended by Jordá (2005). Throughout the analysis, we use 90% confidence intervals.

As mentioned above, an advantage of local projections is that they offer a convenient way to account for nonlinear, state-dependent behavior. In our case, we seek to investigate whether the response of airline stock prices on day \( t \) depends on the magnitude of the COVID-19 shock. Equation (1) can be easily extended to allow the parameters to change depending on the severity of the COVID-19 pandemic on a given day, as:

\[
y_{t+h} = I_s \left[ \alpha_s + \beta_s I_t y_{t-d} \right] + (1-I_s) \left[ \alpha_l + \beta_l I_t y_{t-d} \right] + \epsilon_{t+h}, \quad h = 0, 1, 2, \ldots, H - 1
\]

where \( I_s \) is a dummy variable such that:

\[
I_s = \begin{cases} 
1 & \text{for LARGE COVID-19 changes} \\
0 & \text{for SMALL COVID-19 changes} 
\end{cases}
\]

In equation (1), the subscripts, \( L \) and \( S \), respectively indicate days of large and small COVID-19 changes. We provide details of the methodology used to characterize daily COVID-19 changes as large or small in the next subsection.

Structural impulse responses in the large and small COVID-19 regimes can be estimated as:

\[
\hat{IRF}_L(t, h, d_t) = \hat{\beta}_{1L} \epsilon_{t+d_t} \\
\hat{IRF}_S(t, h, d_t) = \hat{\beta}_{1S} \epsilon_{t+d_t}
\]

where, as with the linear case, we normalize \( \hat{\beta}_{1L} = 1 \) and \( \hat{\beta}_{1S} = 1 \). Confidence intervals for the impulse responses (5) and (6) are constructed in a similar manner to the linear case described above. To present the responses in levels, all the impulse responses shown in the paper are the cumulative impulse response functions. Linear, and state-dependent local projections have been employed by Auerbach and Gorodnichenko (2012), Owjyang et al. (2013) and Ramey and Zubairy (2018) to study the effects of government spending shocks; Zidar (2019) on the growth and employment effects of income tax changes; Coibion et al. (2017), and Alpanda and Zubairy (2019) on the impacts of monetary policy shocks.

### 2.2.2. Definition of “large” versus “small” COVID-19 shocks

We now discuss how we estimate the threshold that characterizes a COVID-19 shock as large or small. Since an arbitrary threshold (such as the mean or median values) is likely to be subject to disagreement, we apply the threshold autoregressive (TAR) model of Hansen (1996) and Gonzalo and Pitarakis (2002). Specifically, we estimate the two-regime self-exciting TAR (SETAR(2)) model:

\[
c_t = Y_t \phi^{(S)} (1 - I(c_{t-d} \leq \tau)) + Y_t \phi^{(L)} I(c_{t-d} > \tau) + \omega_t
\]

where \( c_t \) denotes the percentage change in COVID-19 cases on day \( t \); \( Y_{t-1} = (1, c_{t-1}, c_{t-2}, \ldots, c_{t-p}) \); \( p \) is the lag order; \( \phi^{(S)} = (\phi^{(S)}_1, \phi^{(S)}_2, \ldots, \phi^{(S)}_p) \) and \( \phi^{(L)} = (\phi^{(L)}_1, \phi^{(L)}_2, \ldots, \phi^{(L)}_p) \) are the vectors of coefficients in the “small” and “large” COVID-19 regimes, respectively; \( I (\cdot) \) is an indicator function; \( d > 0 \) is the delay parameter that reflects the idea that there is some lag between the time the COVID-19 shock hits and the time it takes for economic agents to respond to it; \( \tau \) is the threshold value that separates the regimes; and \( \omega_t \sim iid(0, \sigma^2) \). This model, therefore, assumes that below some threshold, \( \tau \), changes in
COVID-19 cases follow an AR(p) process with slope coefficients $\phi^S$, but above this threshold, changes in COVID-19 follow a different AR(p) process with slope coefficients $\phi^L$.

Our goal in this subsection is to estimate the threshold value, $\tau$. This is in contrast to many studies that apply the SETAR model, where the primary interest is to test the null hypothesis of linearity $H_0: \phi^S = \phi^L$ against a threshold effect $H_1: \phi^S \neq \phi^L$. These studies view $\tau$ (and $d$) only as nuisance parameters. Because $\tau$ and $d$ are unidentified under $H_0$, however, standard Lagrange Multiplier, Likelihood Ratio (LR), or Wald tests are not appropriate for testing $H_0: \phi^L = \phi^S$ against $H_1: \phi^L \neq \phi^S$. Hansen (1996) develops a procedure that simultaneously estimates the values of $\tau$, $d$ and the coefficients $\phi^S$ and $\phi^L$ via a grid search over a reasonable range of values of $\tau \in T_j = [\tau_0, \tau_1, \ldots, \tau_J]$ and $d \in [1, D]$, where $j = 1, 2, \ldots, J$; $T_j$ are the possible threshold values; and $D$ is some upper bound (typically $D = p$). Sequential least squares is then used to estimate the model, and the values of $\tau$ and $d$ are those that minimize the Akaike Information Criterion (AIC), Schwartz Information Criterion (SIC), or any such criteria. To obtain reliable estimates of $\phi^S$ and $\phi^L$, Hansen (1996) recommends that the allowable threshold values should be such that each regime should have a sufficiently large number of observations. Once the values of $\tau$ and $d$ are determined,
testing the null of linearity against threshold effects is performed using the sup - LR test suggested by Hansen (1996). Caner and Hansen (2001) show that trimming 15% of the top and bottom quantiles of the threshold variable provides a reasonable trade-off between the power and size of this test. The test has a nonstandard asymptotic distribution under the null hypothesis. However, its approximate asymptotic distribution has been derived by Hansen (1996). Bachmeier (2008) has

Table 1
Payload Allocation and Stock Prices - Dependent Variable is Airline Stock Price.

|          | (1)       | (2)       | (3)       | (4)       |
|----------|-----------|-----------|-----------|-----------|
| Panel A  |           |           |           |           |
|          |           |           |           |           |
| Passenger payload share | 65.53***  | 85.25***  | 22.25***  | 22.25**   |
|          | (2.683)   | (3.609)   | (1.767)   | (7.832)   |
| Flight completion rate | 31.26***  | 10.64***  | 10.64     | 0.292     |
|          | (0.831)   | (0.402)   | (7.523)   | (0.101)   |
| Constant | −18.63*** | −67.86*** | −15.48**  | −15.48*   |
|          | (2.658)   | (3.624)   | (1.792)   | (7.771)   |
| Carrier fixed effects | x         | x         |           |           |
| Carrier clustered standard errors | x         | x         |           |           |
| Observations | 178,682  | 157,786   | 157,786   | 157,786   |
| $R^2$    | 0.003     | 0.013     | 0.782     | 0.782     |
| Panel B  |           |           |           |           |
|          |           |           |           |           |
| Freight payload share | −59.54*** | −74.08*** | −23.17*** | −23.17**  |
|          | (3.116)   | (4.288)   | (2.068)   | (8.298)   |
| Flight completion rate | 31.56***  | 10.62***  | 10.62     |           |
|          | (0.832)   | (0.402)   | (7.544)   |           |
| Constant | 46.66***  | 16.80***  | 6.673**   | 6.673     |
|          | (0.940)   | (0.804)   | (0.408)   | (7.277)   |
| Carrier fixed effects | x         | x         |           |           |
| Carrier clustered standard errors | x         | x         |           |           |
| Observations | 178,682  | 157,786   | 157,786   | 157,786   |
| $R^2$    | 0.002     | 0.011     | 0.782     | 0.782     |

The equations are estimated using Ordinary Least Squares. Fixed effects are included in each specification but were not reported for brevity. Standard errors are in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

Fig. 5. Monthly Passengers at Carrier’s Primary Hub versus other airports.
Notes: Data collected from the US Department of Transportation, Jan 2020 - Mar 2021

Notes: Data collected from the US Department of Transportation, Jan 2020–Mar 2021
3. Empirical results

We first discuss the results for the linear specification (1) in Section 3.1. In Section 3.2, we consider the possible wealth effects of our main empirical findings presented and discussed in Section 3.1. In Section 3.3, we consider the state-dependent responses of U.S. airline stock prices. All responses are the cumulative response functions to a 1% COVID-19 shock. Confidence intervals for the impulse responses are the 90% confidence intervals constructed as described in Section 2.2.

3.1. Linear effects of the COVID-19 pandemic on US airline stock prices

Fig. 3 displays the impulse response functions of the Arca Airline index, and the stock prices of the eleven publicly traded U.S. airlines.

Notes: Data collected from the US Department of Transportation, Jan 2020 - Mar 2021

Fig. 6. Monthly Departures Performed at Carrier’s Primary Hub versus other airports.
Notes: Data collected from the US Department of Transportation, Jan 2020–Mar 2021

3.2. Wealth effects of our main empirical findings

Fig. 7 displays the daily jet fuel prices and monthly air transportation sector employment.

Notes: Source: Data collected from FRED

Fig. 7. Monthly Jet Fuel Prices and Monthly Air Transport Sector Employment.
Notes: Source: Data collected from FRED.
considered in this paper. Following an unexpected increase in COVID-19 cases by 1%, the Arca airline index falls by 0.1 percentage points on impact. This contemporaneous decline is clearly significantly different from zero. Furthermore, the impact of the COVID-19 shock is persistent, lasting longer than two weeks after the COVID-19 shock. Fifteen days after the shock, the Arca Airline index decreases by almost 0.6 percentage points. In general, the responses of the individual airline stock prices display similar dynamics, although there is clearly some heterogeneity. In particular, all airline stock prices display quantitatively and qualitatively similar contemporaneous responses and short-run dynamics: stock prices falls by approximately 0.1 percentage points in all cases, and decline persistently after the shock. There is, however, some degree of heterogeneity in the persistence of the COVID-19 shock. Specifically, the effect of the shock is quite persistent for Alaska Airlines, Allegiant Air, American Airlines, Delta Air Lines, Hawaiian Airlines, JetBlue Airways, Southwest Airlines, Mesa Airlines, Spirit Airlines, and United Airlines, whereas for SkyWest Airlines, the impact of the shock dies out relatively quickly. While this significant decline in airline stock prices is not necessarily unexpected, the novelty of our findings is that it represents the first attempt to quantify the dynamic effect of a COVID-19 shock on U.S. airline stock prices.

Airline stock price responses reflect investors’ integration of public information about COVID-19 and the ensuing containment measures taken by airlines. Although the COVID-19 shock has been universal, not all airlines have been affected in the same way, nor have they all reacted similarly. Our results show some heterogeneity in stock price responses across airlines.

Though part of the differences in stock price response can be

Fig. 8. Response of jet fuel prices to a COVID-19 shock.
Notes: Shaded gray areas represent the 90% confidence intervals.

Fig. 9. Response of airline stock prices to a jet fuel price shock.
Notes: Shaded gray areas represent the 90% confidence intervals.
attributed to nationwide mitigation measures and economic policies implemented during the pandemic, airline-specific characteristics may also be an important source of heterogeneity. Anecdotal evidence suggests that airline characteristics such as payload allocation to cargo versus passengers in response to falling demand, COVID-19 infection rate and lockdown rule in a city considered a primary hub for a given airline, and airline face mask policies, among other factors, influence stock prices.

On payload allocation, airlines that combine air freight with passengers within their operations may have an advantage in their response to the pandemic. For example, American Airlines added hundreds of cargo-only flights in September 2020 to compensate for forgone passenger revenue due to the pandemic.9

Moreover, SkyWest, whose stock prices suffered mildly, had also increased its freight intake to create additional cargo revenue during the crisis, and has recently asked the Federal Aviation Administration (FAA) to prolong a rule that allows carriers to temporarily reconfigure passenger aircraft to cargo operations as demand stays weak due to the pandemic.10

The change in payload allocation we describe above is supported by Fig. 4, right panel, which shows the increase in freight payload share in the thick of the pandemic as the passenger payload share falls. Furthermore, the left panel of Fig. 4 shows the negative relationship between the share of payload allocated to freight and stock prices. We also run regressions to capture the relationship between stock prices and payload allocation in Table 1. Panel A evaluates the effect of passenger payload share on stock price while Panel B examines the effect of freight payload allocation in Table 1. Panel A evaluates the effect of passenger.

Airport disruption, and airline and time fixed effects. The results support the positive association between passenger payload share and stock prices. The pandemic forced airlines to reduce passenger payload and increase freight payload. The switch to freight mitigated some of the passenger revenue losses.

Covid-induced disruptions at airlines’ hub airports may have adverse effects on airline stock prices. Monmousseau et al. (2020) note that the number of tweets from Alaska Airlines’ passengers containing the keyword “cancel” had early spikes connected to early U.S. cases of COVID-19 first discovered on the U.S. West Coast which encompasses Alaska Airlines’ main hub. This may explain the persistence of the negative stock price response experienced by Alaska.

We examine the effects of COVID-induced airport disruption by investigating differences in airline operations at hub airports compared to other airports. For example, the west coast of the US was hit very hard at the onset of the pandemic and Alaska Airlines primary hub is in Seattle (SEA). As such, we can compare Alaska Airlines’ operations at these airports to operations at Alaska’s operations at other airports. We conduct similar analyses for American at JFK, Delta in Atlanta and United in Newark. Consistent with our expectations, Figs. 5 and 6 show that operations (measured by passengers transported and departures performed) at the primary hub of these carriers were severely impacted relative to operations they conducted at other airports.

Allegiant’s dramatic stock price decrease may be the result of the airline’s reluctance to require passengers to wear face masks at the onset of the pandemic. The airline eventually succumbed to public pressure and imposed the wearing of face mask on July 2, 2020, making Allegiant one of the last airlines to require passengers to wear face masks.11

Though the observations above may explain the heterogeneity in airline stock price responses to a COVID-19 shock, we admit that a rigorous empirical analysis is warranted as a natural extension of this paper. Such an extension would explore the role of additional determinants that are likely to influence investors’ behavior such as carrier size (large carriers are expected to have better access to financing to weather the pandemic), quarterly earnings and balance sheet structure. Other less tangible determinants worthy of investigation may include carrier’s network integrity to COVID-19 cases, optimism and sentiment towards airlines. Investors are sensitive to the prevalence of COVID-19 cases and their impact on air travel, however, credit facilities, government guarantees, mask mandate, and lockdown measures seem to have mitigated further decline in stock prices (Capelle-Blancard and Desroziers, 2020).

We also provide evidence, both anecdotal and empirical, that the decline in airline stock prices is not a response to increasing (variable) costs that decrease airline profitability and stock prices. Labor and jet fuel represent the largest cost to airlines, on average, accounting for approximately 35% and 18% of the total of airlines’ operating expenses, respectively.12 As shown in Fig. 7A, jet fuel prices dropped from $1.74 at

Table 2
Estimated Loss in Wealth from a COVID-19 Shock (millions of dollars).

| Days | Alaska | Allegiant | American | Delta | Hawaiian | Jet Blue | Southwest | Mesa | SkyWest | Spirit | United |
|------|--------|-----------|----------|-------|----------|----------|-----------|------|---------|--------|--------|
| 0    | 9.4    | 3.5       | 102.5    | 58.7  | 1.9      | 14.0     | 21.7      | 0.8  | 2.1     | 25.6   | 118.8  |
| 1    | 9.8    | 2.8       | 93.3     | 75.4  | 2.3      | 14.5     | 22.1      | 1.0  | 2.0     | 25.8   | 131.9  |
| 2    | 15.4   | 5.2       | 127.4    | 121.3 | 3.3      | 19.8     | 38.0      | 1.5  | 3.8     | 35.4   | 208.6  |
| 3    | 21.8   | 6.5       | 178.4    | 177.0 | 4.8      | 28.0     | 60.3      | 1.8  | 4.2     | 53.7   | 289.0  |
| 4    | 26.4   | 7.5       | 217.1    | 205.8 | 5.4      | 36.2     | 74.2      | 1.9  | 5.1     | 63.2   | 317.5  |
| 5    | 32.4   | 9.7       | 254.6    | 245.1 | 6.4      | 44.2     | 93.5      | 2.5  | 6.3     | 80.7   | 392.5  |
| 6    | 33.0   | 9.1       | 241.8    | 267.2 | 6.8      | 45.8     | 94.4      | 2.6  | 6.4     | 80.9   | 412.8  |
| 7    | 40.4   | 12.2      | 302.3    | 328.6 | 7.8      | 53.5     | 115.4     | 3.1  | 8.4     | 95.2   | 506.0  |
| 8    | 46.3   | 13.5      | 374.8    | 390.4 | 9.2      | 61.6     | 133.3     | 3.5  | 8.4     | 110.6  | 590.2  |
| 9    | 50.5   | 15.3      | 429.7    | 423.7 | 10.0     | 70.2     | 144.6     | 3.7  | 8.9     | 117.2  | 623.3  |
| 10   | 53.0   | 16.7      | 471.6    | 454.4 | 10.7     | 76.2     | 159.3     | 4.1  | 9.0     | 125.0  | 660.6  |
| 11   | 50.5   | 15.6      | 433.4    | 456.8 | 10.4     | 70.4     | 156.0     | 4.0  | 8.3     | 117.9  | 643.6  |
| 12   | 53.4   | 17.0      | 455.3    | 475.7 | 10.4     | 71.1     | 162.2     | 4.1  | 9.3     | 121.7  | 669.3  |
| 13   | 52.3   | 17.4      | 451.3    | 487.2 | 10.4     | 70.4     | 168.5     | 4.0  | 8.1     | 120.5  | 677.5  |
| 14   | 54.6   | 18.2      | 500.3    | 511.7 | 10.7     | 76.0     | 183.6     | 4.2  | 8.5     | 124.6  | 712.8  |
| 15   | 55.9   | 19.3      | 523.3    | 525.9 | 11.1     | 79.9     | 194.3     | 4.3  | 9.0     | 131.7  | 725.1  |

11 https://www.wbur.org/hereandnow/2020/05/19/legendary-air-face-masks.
12 Airlines for America. A4A Passenger Airline Cost Index (PACI). Available online: https://www.airlines.org/dataset/a4a-quarterly-passenger-airline-cost-index-u-s-passenger-airlines/(accessed on 31 May 2020).

9 https://www.dallasnews.com/business/airlines/2020/08/18/american-airlines-ramps-up-cargo-only-trips-to-1000-flights-in-september/.
10 https://www.faa.gov/documentLibrary/media/Notice/N_8900.546.pdf.
the start of our sample period, to $1.10 at the end of the period - a decrease of more than 36%. The figure further shows that airline employment in March 2021 was almost 20% lower than in January 2020 (7B). Hence, (variable) costs to airlines have generally decreased since the start of the pandemic.

Going beyond anecdotal evidence, we now show that the decrease in jet fuel prices observed in Fig. 7A can in part be attributed to COVID-19 shocks, and that this decline raises airline stock prices. Specifically, Fig. 8 shows that jet fuel prices instantaneously fall by 0.1% in response to a COVID-19 shock. The decrease is significantly different from zero throughout, and the effect of the shock grows as the forecast horizon lengthens. This decrease in a major cost source is likely to be viewed favorably by airline industry investors and stock market participants. If this is indeed the case, then we expect that a jet fuel price shock should increase airline stock prices. Fig. 9 confirms that this is in fact the case. A jet fuel price shock leads to a rise in all airline stock prices, although the positive impact lasts for only a few days. These findings suggest that the decline in airline stock prices cannot be attributed to a decrease in profitability associated with increases in the operating variable costs to U.S. airlines. If anything, a decrease in revenues due to fewer revenue paying passengers explains these findings. To add more credence to this result, we include a year worth of pre-pandemic data to capture the natural relationship between fuel price and airlines’ stock prices. As shown in Fig. A1 in the Appendix, this relationship is somewhat consistent with the post-pandemic relationship between fuel price and airline stock price, reinforcing the fact that airline stock prices are primarily affected by the COVID-induced fall in air travel demand.

Our empirical results are consistent with complimentary evidence found in Alfaro et al. (2020). Using daily data, Alfaro et al. (2020) find that unexpected changes in predicted COVID-19 infections forecast next-day stock returns. They further show that industries that are more vulnerable to exposure to the virus, such as the Accommodations, Entertainment and Transportation industries, experience the largest declines in their market value. They also document evidence that firms that are more labor-intensive, more profitable, and have low debt, experience smaller decreases in their market values in response to the COVID-19 pandemic. They assert that their findings signal that investors expect that losses experienced by firms which can more easily reduce their costs by, for instance, furloughing and/or laying off employees, will be relatively smaller than capital-intensive firms that are unable to shed much of their costs, even as revenues diminish during adverse economic times. The negative, statistically significant, large, and persistent responses of the airline stock prices to a COVID-19 shock that we estimate certainly support this assertion.

3.2. Wealth effects of a COVID-19 shock

An interesting question at this juncture is: how do these negative stock price responses from a COVID-19 shock translate into overall wealth effects for investors? In other words, we contextualize our results by extrapolating monetary estimates of loss in investors’ wealth due to a COVID-19 shock. In our dataset, we observe the daily trading volume of each airline’s stock. This allows us to measure the daily loss in market capitalization for each airline as a result of a COVID-19 shock. In Table 2, we show the loss in wealth incurred by investors on impact and up to 15 days. It is clear from the table that owning airline stocks appeared to be a risky proposition that has been hazardous to investors’ wealth. The COVID-19 pandemic has been more devastating for investors that own legacy carriers’ stocks. In absolute terms, United lost the largest market value ($119 million) on impact reaching $725 million 15 days after the COVID-19 shock. American and Delta suffered comparable market value losses reaching $523 and $526 million, respectively, 15 days after the COVID-19 shock. On the other end of the spectrum, Mesa, SkyWest and Hawaiian suffered relatively mild losses in market value. In any case, it is clear that many investors experienced wealth losses as a result of their airline stock holdings.

3.3. Does the magnitude of the COVID-19 shock matter?

An important question of this paper is whether the response of airline stock prices depends on the size of the COVID-19 shock. To answer this question, we separate COVID-19 shocks into large and small shocks. In Section 2.2.2, we described the methodology used to estimate the threshold value that separates COVID-19 shocks into large versus small shocks. As discussed in that section, the percentage change in daily COVID-19 cases is used as the threshold variable, and a grid search is performed over the set of all possible threshold values. The value of the estimated threshold is the one that minimizes the pooled-AIC. Fig. 10 shows the results of the grid search. As shown in the figure, a daily change of 7.7% or more in COVID-19 cases is considered to be a “large” COVID-19 shock.

Using this threshold value, Fig. 11 presents estimates of the state-dependent model. The dashed lines in the figure represent the airline stock price responses to a small COVID-19 shock, whereas the solid lines are the responses to a large COVID-19 shock. The corresponding 90% confidence intervals are given by the light gray and dark gray shaded areas. As can be observed in Fig. 11, the response of airline stock prices is negative and significantly different from zero for both a large and a small COVID-19 shock. The contemporaneous responses to large and small shocks are quantitatively similar, however, large COVID-19 shocks tend to generate larger declines. For the stock prices of Alaska Airlines, Allegiant Airlines, Delta Airlines, Hawaiian Airlines, JetBlue Airways, Mesa Air Group, Spirit Airways, United Airlines and the Arca Airline Index, large shocks elicit responses that are significantly different from those of small shocks. For the stock prices of the remaining airlines, the responses are not significantly different from each other, as the confidence intervals always overlap. Our results here imply that while a COVID-19 shock leads to a fall in airline stock prices, for some airlines the responses tend to be larger for large COVID-19 shocks.

13 It is worth noting that during the first quarter of 2020, the Organization of the Petroleum Exporting Countries (OPEC) and Russia have been roleing in protracted negotiations and failing to agree on how much production to cut amid the COVID-19 outbreak. This failure to reach an agreement caused oil markets to tank 20% (Tan, 2020). This, in large part, contributed to the considerable drop in jet fuel prices we observe.
3.4. Accounting for the mitigating effects of a mask mandate

It is conceivable that a mask mandate may lower the infection rate of COVID-19, which may mitigate the effect of a COVID-19 shock. Current experimental and epidemiological studies suggest that the use of masks decreases the transmission of COVID-19 (Eikenberry et al., 2020; Greenhalgh et al., 2020). If this is the case, we reckon that the stock price responses to a COVID-19 shock we observe are potentially moderated by the use of masks. To verify this possibility, we conduct a quasi-event study where we generate airline stock price impulse responses to a COVID-19 shock following a mask mandate and compare these results to our original results (solid line) versus after the imposition of a mask mandate (dashed line) in the state of New York. Though requiring face mask use could help in mitigating the spread of COVID-19 (Lyu and Wehby, 2020), the general findings in Fig. 12 suggest that the mask mandate had no significant effect on airline stock prices since the impulse responses generally overlap. This indicates that investors are indifferent in their response to COVID-19 with or without the imposition of a mask mandate. We find similar results when a mask mandate is imposed in California and Texas (see Figs A2 and A3 the Appendix).

Admittedly, there are caveats to our estimation. First, we are unable to observe mask mandate compliance. Second, and relatedly, we do not observe mask mandate enforcement. Third, prior to the official date of statewide mask mandate, multiple counties in California and Texas, for example, had passed localized mask mandates. However, we argue that health guidelines related to COVID-19 from state departments of public health were public knowledge to investors as these mainly reflect the CDC guidelines and consequently localized measures might not necessarily add further information or impact.

Furthermore, since New York imposed a mask mandate on April 17, 2020 while Texas followed suit on July 2, 2020, we are able to use the 53

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Notes: Dark gray shaded areas represent the 90% confidence intervals for large COVID-19 shocks while light gray shaded areas are the corresponding confidence intervals for small shocks.

Fig. 11. State-dependent effects of a COVID-19 shock.

Notes: Dark gray shaded areas represent the 90% confidence intervals for large COVID-19 shocks while light gray shaded areas are the corresponding confidence intervals for small shocks.
stock trading days (not counting weekends) in-between to study the mitigating effects of a mask mandate. During those 53 days, New York had a mask mandate while Texas did not. We also select two airlines with large hub operations in the two states: United Airlines at Newark Liberty Airport serving the New York City metropolitan area and Southwest Airlines which has two hubs (Dallas and Houston) in Texas. We proceed to measure the stock price response of United Airlines, a carrier that operated a large scale operations serving New York, a state that imposed mask mandate, versus measuring the stock price response of Southwest, a carrier that possesses a large share of its operations in the state of Texas, a state that had no mask mandate during the 53 days. Again, the results reported in Fig. A4 in the Appendix support investors’ indifferent attitude towards the mask mandate.

We also examine whether there exist some vaccine mitigation effects on stock price responses in the post-vaccine time period of our sample. Fig. A5 in the Appendix shows no statistical difference in stock price responses (pre- versus post-vaccine) suggesting that investors had priced in the vaccine roll-out in their decision process.

4. Conclusion

By all accounts, the COVID-19 pandemic has had a significant impact on the U.S. airline industry. While the immediate actions of the U.S. federal government prevented insolvency of the industry, domestic and international travel restrictions, and decreased demand for air travel by passengers apprehensive about the pandemic, have led to considerable declines in revenues, profitability, and stock prices of U.S. airlines. This paper represents the first attempt to quantify the magnitude and persistence of the effects of the pandemic on U.S. airline industry stock prices. We do so using daily data on the stock prices of eleven U.S. airlines, as well as a summary measure of U.S. airline stock prices for the period January 21, 2020 to March 15, 2021. Empirically, we employ the method of local projections.

Our analysis yields five important findings. First, a COVID-19 shock leads to an immediate fall in airline stock prices. For all stock prices considered, the contemporaneous response to a 1% COVID-19 shock is a drop of approximately 0.1% on average. Second, this negative response of airline stock prices persists beyond the day in which the shock occurs. In fact, for most airline stock prices, the effect of the COVID-19 shock lasts longer than two weeks, with the peak decline of about 0.6% occurring fifteen days after the shock. Third, we find that this negative response is partly explained by a decrease in air travel demand, which in turn decreased airlines’ revenues and profitability. Fourth, we find some evidence that the size of the COVID-19 shock matters for the response of airline stock prices. Our results show that a large COVID-19 shock tends to elicit a larger and more persistent response than a small COVID-19 shock, although this is not the case for all airline stock prices. Fifth, we estimate the loss in investors’ wealth due to a COVID-19 shock and find that, for instance, United’s investors lost wealth equivalent to $119 million on impact reaching $725 million 15 days after the COVID-19 shock. The cumulative effect of the COVID-19 shock on investors’ wealth is approximately $775 million.

Notes: Dark gray shaded areas represent the 90% confidence intervals for COVID-19 shocks while light gray shaded areas are the corresponding confidence intervals for COVID-19 shocks following mask mandate.

Fig. 12. Response of Airline Stock Prices to a COVID-19 Shock accounting for the New York Mask Mandate.

Notes: Dark gray shaded areas represent the 90% confidence intervals for COVID-19 shocks while light gray shaded areas are the corresponding confidence intervals for COVID-19 shocks following mask mandate.
Our conclusions have a number of implications. First, the slew of heightened health risk mitigation procedures (e.g., temperature checks, deep cleaning between flights, and social distancing during boarding) enacted by airlines/airports may not have been very effective in restoring the confidence of travelers, airline investors, and stock market participants. In fact, these procedures have led to longer airport access and egress times compared to the pre-pandemic period. Second, as states begin to lift stay-at-home orders and reopen their economies, the U.S. airline industry is expected to continue struggling due to lingering fears of a third COVID-19 wave, which may continue to deter passengers from flying and investors from purchasing airline stocks.

Author statement

Bebonchu Atems: Conceptualization, Methodology, Software, Data curation.

Jules Yimga: Data curation, Writing- Original draft preparation, Writing- Reviewing and Editing.

Appendix

Notes: Shaded gray areas represent the 90% confidence intervals

Fig. A1. Response of Airline Stock Prices to a Jet Fuel Price Shock (Pre-COVID).

Notes: Shaded gray areas represent the 90% confidence intervals.
Fig. A2. Response of Airline Stock Prices to a COVID-19 Shock accounting for the California Mask Mandate.

Notes: Dark gray shaded areas represent the 90% confidence intervals for COVID-19 shocks while light gray shaded areas are the corresponding confidence intervals for COVID-19 shocks following mask mandate.
Notes: Dark gray shaded areas represent the 90% confidence intervals for COVID-19 shocks while light gray shaded areas are the corresponding confidence intervals for COVID-19 shocks following mask mandate.

Fig. A3. Response of Airline Stock Prices to a COVID-19 Shock accounting for the Texas Mask Mandate.
Notes: Dark gray shaded areas represent the 90% confidence intervals for COVID-19 shocks while light gray shaded areas are the corresponding confidence intervals for COVID-19 shocks following mask mandate.
**Fig. A4.** Response of Airline Stock Prices to a COVID-19 Shock controlling for Mask Mandate - United versus Southwest.  
**Notes:** Dark gray shaded areas represent the 90% confidence intervals for COVID-19 shocks between April 17, 2020 and July 2, 2020 when New York had a mask mandate and Texas did not. United has hub operations in New York via Newark Liberty Airport and Southwest has hub operations in Texas via Dallas and Houston.
Fig. A5. Response of Airline Stock Prices to a COVID-19 Shock accounting for Post-Vaccine Period.

Notes: Dark gray shaded areas represent the 90% confidence intervals for COVID-19 shocks while light gray shaded areas are the corresponding confidence intervals for COVID-19 shocks following vaccine administration.

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