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The airline on-time performance impacts of the COVID-19 pandemic

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ABSTRACT
This paper examines the effects of the COVID-19 pandemic on flight delays in the U.S. airline industry. Using daily data on COVID-19 cases and flight on-time performance, and controlling for product, carrier and market characteristics, we find that increases in reported COVID-19 cases are associated with reductions in both departure and arrival delays. Specifically, a standard deviation increase in COVID-19 cases reduces arrival delay by 1 min 42 s and departure delay by 2 min, on average. Our results suggest that despite the economic fallout from the pandemic, a silver lining emerges—flights are departing and arriving with less delay amid the pandemic.

Introduction

On December 9, 2019, the first case of coronavirus 2019 (COVID-19) was recorded in Wuhan, China (Huang et al., 2020). The virus rapidly spread beyond China causing an unprecedented global health crisis that led to economic hardship and disruption across many industries. In the United States, the National Bureau of Economic Research determined that the U.S. economy officially entered a recession in February 2020. The Bureau notes that:

“...the unprecedented magnitude of the decline in employment and production, and its broad reach across the entire economy, warrants the designation of this episode as a recession, even if it turns out to be briefer than earlier contractions.”

Between February and April 2020, the U.S. economy lost 22 million jobs resulting in a sharp increase in the unemployment rate to 14.7% (Handwerker et al., 2020). In response to this economic downturn, the Coronavirus Aid, Relief, and Economic Security (CARES) Act² and the Coronavirus Response and Relief Supplemental Appropriations Act³ were passed by the U.S. Congress to deliver immediate economic support to workers, families, and small businesses. More recently, a budget resolution for a $1.9 trillion stimulus package was approved on February 27, 2021.⁴

Even though the COVID-19 pandemic had dire economic outcomes across industries, its effects on the U.S. airline industry have been particularly damaging, with projections that seem to indicate that the industry is unlikely to return to 2019 passenger volumes before 2023–2024 (Airlines for America, 2021).

Data from the Transportation Security Administration (TSA) indicate that only about 95,000 passengers were screened across U.S. airports on April 16, 2020, at the onset of the pandemic. For comparison, that number represents a 96% decline from 2.6 million passengers on the same day the year before.

This paper examines the impact of COVID-19 on airline on-time performance. In our view, this research question is worthy on two accounts. First, the sharp decrease in domestic air traffic and the uncertainty surrounding the COVID-19 pandemic make the airline industry a suitable candidate to answer important questions about product quality amid a pandemic. Second, on-time performance is a clear-cut measure of product quality that has been used by several studies (Prince and Simon, 2009; Mazzeo, 2003). Consumers care about flight on-time performance and in some instances are willing to pay for it (Yimga and Gorjidooz, 2019; Gayle and Yimga, 2018). Airlines recognize the importance of on-time performance (OTP) and have proudly brandished their OTP ranking as a powerful marketing tool.⁵

In our empirical analysis, we make the following contributions. First, we use high frequency (daily) data to evaluate the impact of COVID-19 pandemic on flight delay. Second, we control for hour of the day, day of the week in addition to factors that are likely to influence OTP through a series of fixed effects models. Third, we examine

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1 Business Cycle Dating Committee (2020).
2 Coronavirus Aid, Relief, and Economic Security Act, S. 3548, 116th Cong. (2020).
3 Coronavirus Response and Relief Supplemental Appropriations Act, H.R. 6074, 116th Cong. (2020).
4 American Rescue Plan Act of 2021, H.R. 1319, 117th Cong. (2021).
5 Boozer, Wyld and Grant (1991) note that American Airlines ran ads calling itself “The On-Time Machine" in the 1990’s. Hawaiian Airlines has been intentional in publicizing itself as the nation’s most punctual carrier for 15 years in the row (Hawaiian Airlines, 2019).

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whether the OTP effects of COVID-19 are sensitive to how OTP is measured.

Flight delays are the result of imbalances between airport/airspace capacity and air travel demand (Skalitsas, 2011). We argue that the impact of COVID-19 on flight delays arises from the relative size of COVID-19 shocks to both airport/airspace capacity and air travel demand. On the one hand, COVID-19 caused a severe decrease in airline traffic across all routes (Dube, Nhamo, and Chikodzi, 2021; Maneenop and Kotcharin, 2020). This creates a situation of excess capacity at airports. The excess capacity releases the stress that may have prevailed in the absence of COVID-19 at congested airports. As a result, OTP is likely to improve.

On the other hand, the COVID-19 outbreak has struck airports severely. In response to the sharp fall in air travel, airlines and airports cut capacity (Sobierański, 2020). Airlines grounded their fleets more or less completely due to the imposed travel restrictions while U.S. airport workers were hit with layoffs. Almost all airlines announced job cuts and/or reduced work schedules. Employment in the industry fell from approximately 512,000 workers in March to roughly 380,000 in June 2020 (Sainato, 2020). If the reduction in capacity outweighs the decrease in traffic, relatively speaking, OTP may worsen. Flight delays may also be exacerbated by COVID-related protective measures at airports that may slow down passenger boarding and offboarding or increase the time it takes to clean or disinfect aircrafts between flights.

We posit that the resulting impact of COVID-19 on OTP ultimately depends on the net effects of the countervailing forces described above. We find a negative relationship between COVID-19 cases and airline flight delay. More precisely, a standard deviation increase in reported COVID-19 cases reduces arrival delay by 1 min 42 s and departure delay by 2 min, ceteris paribus. Using changes in load factor, a proxy that captures COVID-19 shocks on both air travel demand and airline capacity, we show that OTP improves because following a COVID-19 shock, the fall in demand outweighs the decrease in capacity. This relieves some stress on the air transportation (e.g., congestion) resulting in reduced flight delays. To the best of our knowledge, this study is among a very few to estimate the product quality impacts of the COVID-19 pandemic in the airline industry (Hotle and Mumbower, 2021; Kim, 2021; Monmousseau et al., 2020). Our results suggest that despite the economic fallout from the pandemic, a silver lining prevails—flights are departing and arriving closer to their scheduled time in greater numbers despite the COVID-19 shocks.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data sources, key terms and variables used in the paper. Section 4 lays out the empirical model used for analysis. Section 5 reports our findings and section 6 concludes.

Literature review

Measuring product quality has always been a challenge for empirical studies because product quality may entail subjective and objective determinants whose measurement is crucial in evaluating consumer satisfaction (Yimga, 2017).

With respect to the airline industry, some determinants of product quality that are deemed quantifiable have been investigated. These include flight frequency (Brueckner and Luo, 2014; Girvin, 2010; Brueckner and Pai, 2009), the number connecting services and associated layover time (Youssef and Hansen, 1994), airline safety (Rose, 1990), business travelers’ perception of service quality (Goh and Uncles, 2003), and schedule padding (Yimga, 2020a; Yimga and Gorjidooz, 2019), among others. Moreover, product quality can be investigated indirectly using distance-related measures. Empirical work that has examined this kind of itinerary quality measure has often referred to it as air travel (in)convenience. Airline studies that have examined flight on-time performance have focused on its relationship with airline alliance, competition, multimarket contact, prices and entry or threat of entry (Yimga, 2020b; Prince and Simon, 2015; Rupp and Sayanak, 2008; Tiernan, Rhoades, and Waguespack, 2008; Tsantoulis and Palmer, 2008; Forbes, 2008; Mazzeo, 2003).

Closely related studies that have examined changes in airline product quality for passengers during the COVID-19 pandemic include Monmousseau, Marzouli, Feron, and Delahaye (2020) and Hotle and Mumbower (2021). Monmousseau, Marzouli, Feron, and Delahaye (2020) investigate the impact of COVID-19 induced travel restrictions on passenger mood measured by tweets obtained from Twitter. The data from Twitter allow for the construction of four passenger-centric metrics for mood. The findings show heterogeneous responses across airlines to the COVID-19 travel restriction measures from a passenger perspective.

Hotle and Mumbower (2021) examine the COVID-19 impacts on air travel operations and commercial airport service in the United States. Accounting for the financial support received by airports through the CARES Act, the results show asymmetric response in flight departures across airports. Relative to smaller airports, larger airports saw a disproportionate contraction in flight departures leading to greater service reductions. At the same time, airports in multi-airport cities suffered a larger drop in service than airports located in single-airport cities. These findings together point to the fact that in the short term, the minimum service restrictions imposed by the CARES Act have favorably sheltered smallest airports from losing service.

Jarry, Delahaye and Feron (2021) analyze the safety impacts of the COVID-19 pandemic using an energy metric, during the approach and landing phases at Charles De Gaulle airport. The study finds an overall increase in approach phases with excess energy, pointing to an increase in the rate of unbalanced landing during the period of COVID-19.

We contribute to the above literature by examining the effects of COVID-19 on flight departure and arrival delays.6

Data and empirical approach

Data

We collect daily data from January 1, 2020 to September 30, 2020 from three sources. First, 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” (Centers of Disease Control and Prevention, 2020).

Second, domestic flight OTP come from the Airline On-time Performance database maintained by the U.S. Bureau of Transportation Statistics (BTS). This database contains daily flight OTP data for all U.S. domestic carriers making revenues from domestic passenger flights that amount to at least 0.5 percent of total industry revenues. Each flight record contains information on the operating carrier, the origin and destination airports, flight times, the distance in miles for recent studies, see Chen and Gayle (2019) and Gayle and Yimga (2014).

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6 For instance, United Airlines launched United CleanPlus, a program in collaboration with Clorox and Cleveland Clinic. United also provides kits with masks and hand sanitizer wipes (United Airlines, 2020). On April 10, 2020, Delta Airlines adjusted its boarding process to a back-to-front scheme to enforce social distancing (Delta Airlines, 2020).

7 For recent studies, see Chen and Gayle (2019) and Gayle and Yimga (2014).

8 Kim (2021) provides a synthesis of interdisciplinary research on the transportation impacts of COVID-19.
flown, and departure and arrival delay numbers. Third, population data used to measure the size of markets come from the U.S. Census Bureau.

Given the large volume of daily data, we restrict our analysis to traffic performed by only U.S. carriers, across the 55 most populated cities in the continental United States. We provide the list of airports across these cities in Table A1 in the Appendix.

**Market and product**

Following Chen and Gayle (2019), we describe a market as a unidirectional combination of airport pairs. Using airport-pairs to describe a market is fitting for this application as flight OTP is airport-specific. Using city-pairs to characterize a market would not be suitable since a city can have multiple airports with different OTP. Markets are indexed by \( m \) and our sample contains 1,732 markets. A product is defined as a combination of an airline and the type of itinerary (e.g., nonstop). The airlines are indexed by \( a \) and provide a total of 1,882,459 products (or flights) indexed by \( j \). Given the nature of the Airline On-Time Performance database, we are only able to consider nonstop products. The dataset displays individual flights performed with their respective scheduled and actual departure/arrival times. The resulting working sample includes the following 16 carriers: Endeavor Air (9E), American (AA), Alaska (AS), JetBlue (B6), Delta (DL), ExpressJet (EV), Frontier (F9), Allegiant (G4), Envoy Air (MQ), Spirit (NK), PSA Airlines (OH), SkyWest (OO), United (UA), Southwest (WN), Mesa (YV) and Midwest (YX).

**On-time performance**

We directly use measures of OTP from the Airline On-time Performance database curated by the BTS. Though the BTS counts a flight to be late if the flight does not arrive at (depart from) the gate within 15 min of scheduled arrival (departure) time, we consider a flight as late if it arrives after its scheduled time regardless of the number of minutes. Based on the BTS' definition, a flight that is 14 min late would be considered “on-time”. We consider such flights to be 14 min late.

In this paper, we consider two measures of OTP. The first measure is *Arrival Minutes Late*. Our analysis is conducted at the carrier-market-day level. To construct the *Arrival Minutes Late* variable, we average the arrival minutes late of a given carrier over a given market on a particular day. The second OTP measure is the daily market-level number of late-arriving flights by a given carrier. We use analogous measures for departure OTP. Throughout our study, we omit early arrivals/departures since they appear in the dataset as negative delay. However, we are few cases in late March 2020. We directly use measures of OTP from the Airline On-Time Performance database, we are only able to consider nonstop products. The dataset displays individual flights performed with their respective scheduled and actual departure/arrival times. The resulting working sample includes the following 16 carriers: Endeavor Air (9E), American (AA), Alaska (AS), JetBlue (B6), Delta (DL), ExpressJet (EV), Frontier (F9), Allegiant (G4), Envoy Air (MQ), Spirit (NK), PSA Airlines (OH), SkyWest (OO), United (UA), Southwest (WN), Mesa (YV) and Midwest (YX).

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In Figs. 1 and 2, we depict daily fluctuations in COVID-19 cases and OTP. Both figures show a decrease in flight delay as COVID-19 cases spiked in late March 2020. We find similar patterns when we graph the proportion of late flights in Fig. A2 in the Appendix. Fig. 2, in particular, illustrates a dramatic fall in the number of late flights that coincides with the sharp increase in COVID-19 cases in late March 2020. Fig. 3 illustrates late flights across time blocks with a surge and fall in late flights that coincide with early morning and late evening as there are few flights scheduled at those times. Figs. 4 and 5 suggest that midweek flights are more prone to delays.

We also explore OTP heterogeneity across the airports and airport pairs in the sample in Tables A2 and A3 in the Appendix. Dallas Love Field Airport (DAL) and Oakland International Airport (OAK) had the best OTP record with an average arrival delay of 20 min. O'Hare Air-

12 The slot-restricted airports are New York Kennedy (JFK), New York LaGuardia (LGA), Chicago O'Hare (ORD), and Washington National (DCA).

13 Given the absence of passenger volume at the carrier-market level in the databases, we use flight shares.
Baseline model

In the baseline specification, we regress the OTP of product \( j \) by airline \( a \) in market \( m \) in time period \( t \) on COVID-19 and a vector of flight \( (W_{jamt}) \), carrier \( (X_{amt}) \) and market \( (Z_{mt}) \) characteristics:

\[
OTP_{jamt} = \gamma + \tau \cdot \text{COVID}_t + \beta W_{jamt} + \delta X_{amt} + \rho Z_{mt} + \epsilon_{jamt} \tag{1}
\]

The parameter of interest is \( \tau \) which captures the effect of COVID-19 on OTP.

Market Fixed-Effects model

Considering that the baseline specification may be susceptible to changes in unobserved market heterogeneity, our primary interest is to estimate a specification with market fixed effects where \( \theta_m \) controls for market heterogeneity:

\[
OTP_{jamt} = \gamma + \tau \cdot \text{COVID}_t + \beta W_{jamt} + \delta X_{amt} + \theta_m + \epsilon_{jamt} \tag{2}
\]

The fixed-effects specification is favorable on the grounds that the \( \tau \) estimate in Eq. (2) characterizes purely within-market variation, free
of market heterogeneity (Ito and Lee, 2007). Furthermore, the use of high frequency (daily) observations provides some assurances for identification as our estimations are likely not subject to aggregation biases (Ghanem and Smith, 2021). With aggregated data, it is rather intricate to pinpoint precisely the effect of COVID-19, that is, to identify the effect of COVID-19 per se and to eliminate the impact of market heterogeneity taking place in the same time period. When high frequency data is used to measure OTP responses, the precise moment of a COVID shock is known and we are able to correctly identify OTP reactions (e.g., see Fig. 2). This appears to be a solution for not only removing the aggregation bias but also reducing drastically the time interval of the analysis, and thus the number of possible confounding factors. This allows us to remove the noise stemming from other events that might influence OTP.

In our estimation, we account for market-weekday interaction fixed effects, market-time block fixed effects, respectively, to identify the effect of COVID-19 on OTP based on differences in specific markets at a specific time of day. Accounting for market heterogeneity is vital for mitigating potential endogeneity issues. Moreover, the temporal precedence of the COVID-19 pandemic with respect to OTP provides an excellent opportunity to evaluate the response of airline OTP to a credibly exogenous COVID-19 shock.

**Estimation results**

The estimation results of the baseline model are reported in Tables 2 through 5. In these tables, we control for market heterogeneity using a set of market-specific variables without market fixed effects. We report the estimation results of the market fixed effects specification in Tables 6 through 9. Comparatively, the coefficient estimates in the market fixed effects model are slightly larger. As noted in the pre-

![Fig. 3. Late Flights and Hourly Intervals.](image)

![Fig. 4. Late Flights and Weekdays.](image)

![Fig. 5. Average Minutes Late and Weekdays.](image)
vious section, these coefficient estimates capture purely within-market variation free of market heterogeneity. Given that the signs of the coefficients are consistent across specifications, we discuss the results of the market fixed effects specification.

In Tables 6 and 7, the outcome variable, OTP, is measured by arrival delay minutes and the number of late-arriving flights, respectively. The columns in the tables separately control for time block, weekday, and day of the month. In both tables, the coefficient estimate on COVID-19 cases is negative and statistically significant suggesting that increases in COVID-19 cases are associated with reductions in flight delay. More precisely, the coefficient estimate on COVID-19 cases in Table 6, column 1, suggests that, ceteris paribus, a standard deviation increase in COVID-19 cases reduces arrival delay by 1 min 42 s.14

Table A4 in the Appendix shows the findings when the share of late flights is as a proxy for OTP.

As expected, the flight characteristics in Tables 6 and 7 suggest that departure delay and taxi times increase arrival delay while carrier characteristics indicate that low-cost carriers have worse OTP and flights arriving at the operating carrier’s hub tend to be associated with more delay. The findings using departure OTP are consistent with the arrival OTP results although they suffer from a low $R^2$. This is, in part, due to the lack of flight characteristics in the model (Tables 4 and 5).

We did not include the same flight characteristics that were used in the arrival OTP regressions because they must satisfy the “temporal precedence” assumption and pre-boarding information that are likely to impact departure delay are not available. In other words, the low $R^2$ may be the result of omitted variables that are not observable by the researcher.

Tables 8 and 9 evaluate the effect of COVID-19 cases on departure delay minutes and late-departing flights, respectively, and controlling

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14 $-0.1683 \times \ln(23236) \times 60 \text{seconds} = 102 \text{seconds} = 1 \text{min} 42 \text{seconds}$. The standard deviation of daily COVID-19 cases (23,236) appears in the descriptive statistics table, Table 1.
We thank an anonymous referee for this suggestion.

... to prevail, and OTP would worsen.

$\text{OTP}_{\text{jam}} = \text{LoadFactor}_{\text{jam}}(\text{COVID}, M) + \beta W_{\text{jam}} + \delta X_{\text{jam}} + \rho Z_{\text{jam}} + \epsilon_{\text{jam}} \quad (3)$

where $\text{LoadFactor}_{\text{jam}}$ represents the load factor of product $j$ by airline $\alpha$ in market $m$ in time (month) period $t$. $M$ represents some predictors of load factors such as product characteristics. The vectors $W$, $X$, and $Z$ are described as in Eq. (1). We estimate Eq. (3), using a Two-Stage Least Squares approach. In the first stage, we regress load factor on COVID-19 cases. In the second stage, we regress OTP on the predicted values of load factor from the first stage including control variables.

Tables 10 and 11 reports the regression results when we control for load factor. As noted above, COVID-19 impacts OTP via its influence on both air travel demand (passengers) and airline capacity (seats). As expected, in the first-stage regression (columns 1 and 3),
Table 3
Late-arriving Flights Results.

| (1) | (2) | (3) | (4) |
|-----|-----|-----|-----|
| ln (Covid-19 cases) | −0.0087*** | −0.0083*** | −0.0114*** | −0.0071*** |
| (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| Flight Characteristics | | | | |
| Late-departing flights | 0.8017*** | 0.8007*** | 0.7880*** | 0.7979*** |
| (0.0011) | (0.0011) | (0.0011) | (0.0011) |
| Taxi out | 0.0310*** | 0.0313*** | 0.0296*** | 0.0304*** |
| (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Taxi in | 0.0243*** | 0.0244*** | 0.0240*** | 0.0243*** |
| (0.0004) | (0.0004) | (0.0004) | (0.0004) |
| Carrier Characteristics | | | | |
| Origin flight frequency | −0.0948*** | −0.0883*** | −0.0753*** | −0.0871*** |
| (0.0053) | (0.0054) | (0.0053) | (0.0053) |
| Low-cost Carrier | −0.1198*** | −0.1194*** | −0.1217*** | −0.1225*** |
| (0.0048) | (0.0048) | (0.0048) | (0.0048) |
| Into hub | 0.0343*** | 0.0376*** | 0.0412*** | 0.0372*** |
| (0.0046) | (0.0047) | (0.0046) | (0.0046) |
| Market Characteristics | | | | |
| Tourist destination | −0.0786*** | −0.0813*** | −0.0717*** | −0.0754*** |
| (0.0078) | (0.0078) | (0.0078) | (0.0078) |
| Competitive Market | 0.0994*** | 0.1019*** | 0.1061*** | 0.1018*** |
| (0.0042) | (0.0043) | (0.0042) | (0.0042) |
| Market size | 0.0362*** | 0.0407*** | 0.0395*** | 0.0363*** |
| (0.0039) | (0.0039) | (0.0038) | (0.0039) |
| Constant | 0.3598*** | 0.2172*** | −0.0267 | 0.2939*** |
| (0.0647) | (0.0719) | (0.0652) | (0.0648) |
| Departure time block x | | | | |
| Arrival time block x | | | | |
| Day of month | | | | |
| Day of week | | | | |
| Observations | 587,898 | 587,898 | 587,898 | 587,898 |
| R² | 0.55 | 0.55 | 0.55 | 0.55 |

Notes: The data are from the Airline On-Time Performance database, and we restrict the sample to the 55 most populous cities in the Continental United States. *p < 0.10; **p < 0.05; ***p < 0.01.
Source: U.S. Bureau of Transportation Statistics, U.S. Census Bureau, U.S. Centers for Disease Control and Prevention (CDC).

Table 4
Departure Delay Minutes Results.

| (1) | (2) | (3) | (4) |
|-----|-----|-----|-----|
| ln (Covid-19 cases) | −0.2634*** | −0.2553*** | −0.3086*** | −0.2641*** |
| (0.0140) | (0.0141) | (0.0152) | (0.0140) |
| Carrier Characteristics | | | | |
| Origin flight frequency | −6.8909*** | −6.8025*** | −6.8491*** | −6.8790*** |
| (0.1381) | (0.1393) | (0.1379) | (0.1380) |
| Low-cost Carrier | −9.9329*** | −9.9589*** | −9.8912*** | −9.9371*** |
| (0.1143) | (0.1149) | (0.1142) | (0.1142) |
| Out of hub | −3.6595*** | −3.6229*** | −3.6363*** | −3.6538*** |
| (0.1200) | (0.1209) | (0.1199) | (0.1200) |
| Market Characteristics | | | | |
| Tourist destination | 2.6919*** | 2.7648*** | 2.6974*** | 2.6828*** |
| (0.1951) | (0.1960) | (0.1949) | (0.1951) |
| Competitive Market | 2.6082*** | 2.6360*** | 2.6069*** | 2.6023*** |
| (0.1073) | (0.1075) | (0.1072) | (0.1073) |
| Market size | 1.7611*** | 1.8081*** | 1.7540*** | 1.7667*** |
| (0.0971) | (0.0982) | (0.0970) | (0.0971) |
| Slot restricted origin airport | 1.9658*** | 1.9867*** | 1.9108*** | 1.9656*** |
| (0.2521) | (0.2529) | (0.2519) | (0.2521) |
| Constant | 72.3692*** | 71.6669*** | 71.8538*** | 72.4027*** |
| (1.6899) | (1.8659) | (1.7059) | (1.6950) |
| Departure time block x | | | | |
| Arrival time block x | | | | |
| Day of month | | | | |
| Day of week | | | | |
| Observations | 752,019 | 752,019 | 752,019 | 752,019 |
| R² | 0.02 | 0.02 | 0.02 | 0.02 |

Notes: The data are from the Airline On-Time Performance database, and we restrict the sample to the 55 most populous cities in the Continental United States. *p < 0.10; **p < 0.05; ***p < 0.01.
Source: U.S. Bureau of Transportation Statistics, U.S. Census Bureau, U.S. Centers for Disease Control and Prevention (CDC).
COVID-19 negatively affects load factor suggesting that the demand effect is larger than the capacity effect. The second stage (columns 2 and 4) shows a positive relationship between load factor and flight delays. This suggests that lower predicted values of load factor decrease flight delays. Therefore, to calculate the impact of COVID-19 on OTP, we multiply the two coefficient estimates described above.

Thus, Table 11 suggests that a standard deviation increase in reported COVID-19 cases leads to 2 min 40 s reduction in departure delay.\footnote{\[0.0172 \times 15.45 \times \ln(23236) \times 60\text{seconds} = -160\text{seconds} \approx -2\text{min40seconds}.\] The standard deviation of daily COVID-19 cases (23,236) appears in the descriptive statistics table, Table 1.}

| Table 5 | Late-departing Flights Results. |
|---------|----------------------------------|
| (1)     | (2)     | (3)     | (4)     |
| ln (Covid-19 cases) | -0.1821*** | -0.1820*** | -0.1799*** | -0.1774*** |
| (0.0005) | (0.0005) | (0.0006) | (0.0005) |
| Carrier Characteristics |         |         |         |         |
| Origin flight frequency | 0.5487*** | 0.5618*** | 0.5580*** | 0.5550*** |
| (0.0052) | (0.0053) | (0.0052) | (0.0052) |
| Low-cost Carrier | -0.0052 | -0.0123*** | 0.0005 | -0.007 |
| (0.0043) | (0.0044) | (0.0043) | (0.0043) |
| Out of hub | 0.1338*** | 0.1444*** | 0.1360*** | 0.1369*** |
| (0.0046) | (0.0046) | (0.0045) | (0.0045) |
| Market Characteristics |         |         |         |         |
| Tourist destination | 0.1998*** | 0.2241*** | 0.2040*** | 0.2033*** |
| (0.0074) | (0.0074) | (0.0073) | (0.0074) |
| Competitive Market | 0.3592*** | 0.3613*** | 0.3588*** | 0.3579*** |
| (0.0041) | (0.0041) | (0.0040) | (0.0041) |
| Market size | 0.3569*** | 0.3774*** | 0.3556*** | 0.3580*** |
| (0.0037) | (0.0037) | (0.0036) | (0.0037) |
| Slot restricted origin airport | -0.2632*** | -0.2876*** | -0.2726*** | -0.2726*** |
| (0.0096) | (0.0096) | (0.0094) | (0.0095) |
| Constant | -6.5784*** | -7.4121*** | -6.9430*** | -6.7606*** |
| (0.0643) | (0.0708) | (0.0638) | (0.0640) |
| Departure time block | x |         |         |         |
| Arrival time block | x |         |         |         |
| Day of month |         |         |         |         |
| Day of week |         |         |         |         |
| Observations | 752,019 | 752,019 | 752,019 | 752,019 |
| $R^2$ | 0.18 | 0.18 | 0.2 | 0.19 |

Notes: The data are from the Airline On-Time Performance database, and we restrict the sample to the 55 most populous cities in the Continental United States.

*p < 0.10; **p < 0.05; ***p < 0.01.

Source: U.S. Bureau of Transportation Statistics, U.S. Census Bureau, U.S. Centers for Disease Control and Prevention (CDC).

| Table 6 | Arrival Delay Minutes Results, Market Fixed Effects Model. |
|---------|----------------------------------------------------------|
| (1)     | (2)     | (3)     | (4)     |
| ln (Covid-19 cases) | -0.1683*** | -0.1677*** | -0.1668*** | -0.1636*** |
| (0.0084) | (0.0085) | (0.0092) | (0.0085) |
| Flight Characteristics |         |         |         |         |
| Departure min late | 0.8779*** | 0.8779*** | 0.8777*** | 0.8779*** |
| (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| Taxi out | 0.1144*** | 0.1152*** | 0.1128*** | 0.1128*** |
| (0.0041) | (0.0041) | (0.0041) | (0.0041) |
| Taxi in | 0.0644*** | 0.0647*** | 0.0633*** | 0.0630*** |
| (0.0067) | (0.0067) | (0.0067) | (0.0067) |
| Carrier Characteristics |         |         |         |         |
| Origin flight frequency | -3.4236 | -3.4126 | -3.4094 | -3.406 |
| (86210.6796) | (86211.0185) | (86182.4788) | (86197.1501) |
| Low-cost Carrier | 0.4049*** | 0.4050*** | 0.4002*** | 0.3939*** |
| (0.1013) | (0.1017) | (0.1013) | (0.1013) |
| Into hub | -0.0027 | 0.0023 | -0.0015 | 0.0017 |
| (0.1089) | (0.1096) | (0.1089) | (0.1089) |
| Constant | 45.1339 | 45.2892 | 46.0925 | 44.9934 |
| (701832.4102) | (701835.1689) | (701602.8305) | (701722.2673) |
| Market fixed effects | x | x | x | x |
| Departure time block | x |         |         |         |
| Arrival time block | x |         |         |         |
| Day of month |         |         |         |         |
| Day of week |         |         |         |         |
| Observations | 587,898 | 587,898 | 587,898 | 587,898 |
| $R^2$ | 0.78 | 0.78 | 0.78 | 0.78 |

Notes: The data are from the Airline On-Time Performance database, and we restrict the sample to the 55 most populous cities in the Continental United States.

*p < 0.10; **p < 0.05; ***p < 0.01.

Source: U.S. Bureau of Transportation Statistics, U.S. Census Bureau, U.S. Centers for Disease Control and Prevention (CDC).
An alternative measure of COVID-19 spread is the positivity rate—percentage of COVID-19 tests that are positive. Passengers rely on test results to make travel decisions. Public health administrators depend on test results to monitor the pandemic, while policymakers rely on this data to inform shutdown and reopening directives. Higher positivity rates indicate higher infection and community spread. It also gauges whether testing is keeping up with the rate of transmission. Fig. A3 in the Appendix shows that the daily positivity rate and COVID-19 cases are somewhat correlated. We see an increase in positivity rate as the first wave of COVID-19 cases kicks in. The second wave also witnesses an increase in positivity rate though the increase appears to be mild.

| Table 7 | Late-arriving Flights Results, Market Fixed Effects Model. |
|---------|------------------------------------------------------------|
|         | (1)            | (2)            | (3)            | (4)            |
| In (Covid-19 cases) | −0.0193*** | −0.0184*** | −0.0241*** | −0.0180*** |
| Flight Characteristics | (0.0006) | (0.0006) | (0.0007) | (0.0006) |
| Late-departing flights | 0.7819*** | 0.7815*** | 0.7622*** | 0.7765*** |
| | (0.0012) | (0.0012) | (0.0012) | (0.0012) |
| Taxi out | 0.0311*** | 0.0313*** | 0.0297*** | 0.0305*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Taxi in | 0.0164*** | 0.0165*** | 0.0158*** | 0.0163*** |
| | (0.0004) | (0.0004) | (0.0004) | (0.0004) |
| Carrier Characteristics | (5682.5980) | (5681.2693) | (5643.8416) | (5670.5278) |
| Origin flight frequency | 0.3937 | 0.4079 | 0.4154 | 0.4172 |
| Low-cost Carrier | 0.0716*** | 0.0678*** | 0.0689*** | 0.0689*** |
| | (0.0067) | (0.0067) | (0.0066) | (0.0067) |
| Into hub | 0.0174** | 0.0186** | 0.0137* | 0.0164** |
| | (0.0072) | (0.0072) | (0.0071) | (0.0072) |
| Constant | −3.5837 | −3.6274 | −3.938 | −3.7677 |
| | (46261.4544) | (46250.6379) | (45945.9426) | (46163.1925) |
| Market fixed effects | x | x | x | x |
| Departure time block | x | x | x | x |
| Arrival time block | x | x | x | x |
| Day of month | x | x | x | x |
| Day of week | x | x | x | x |
| Observations | 587,898 | 587,898 | 587,898 | 587,898 |
| $R^2$ | 0.57 | 0.57 | 0.58 | 0.58 |

Notes: The data are from the Airline On-Time Performance database, and we restrict the sample to the 55 most populous cities in the Continental United States.
*p < 0.10; **p < 0.05; ***p < 0.01.
Source: U.S. Bureau of Transportation Statistics, U.S. Census Bureau, U.S. Centers for Disease Control and Prevention (CDC).

| Table 8 | Departure Delay Minutes Results, Market Fixed Effects Model. |
|---------|------------------------------------------------------------|
|         | (1)            | (2)            | (3)            | (4)            |
| In (Covid-19 cases) | −0.1957*** | −0.1859*** | −0.2430*** | −0.1980*** |
| Flight Characteristics | (0.0142) | (0.0143) | (0.0154) | (0.0142) |
| Origin flight frequency | 358.5254*** | 359.5072*** | 359.8624*** | 357.3427*** |
| | (124.9795) | (125.0033) | (124.8612) | (124.9692) |
| Low-cost Carrier | −0.8123*** | −0.8764*** | −0.7882*** | −0.8158*** |
| | (0.1710) | (0.1717) | (0.1708) | (0.1709) |
| Out of hub | −0.5069*** | −0.5208*** | −0.5020*** | −0.4970*** |
| | (0.1831) | (0.1840) | (0.1829) | (0.1830) |
| Constant | −2851.3520*** | −2857.5665*** | −2862.2769*** | −2841.5257*** |
| | (1014.6910) | (1014.8870) | (1013.7309) | (1014.6074) |
| Market fixed effects | x | x | x | x |
| Departure time block | x | x | x | x |
| Arrival time block | x | x | x | x |
| Day of month | x | x | x | x |
| Day of week | x | x | x | x |
| Observations | 752,019 | 752,019 | 752,019 | 752,019 |
| $R^2$ | 0.05 | 0.05 | 0.05 | 0.05 |

Notes: The data are from the Airline On-Time Performance database, and we restrict the sample to the 55 most populous cities in the Continental United States.
*p < 0.10; **p < 0.05; ***p < 0.01.
Source: U.S. Bureau of Transportation Statistics, U.S. Census Bureau, U.S. Centers for Disease Control and Prevention (CDC).

**Positivity rate**

An alternative measure of COVID-19 spread is the positivity rate—percentage of COVID-19 tests that are positive. Passengers rely on test results to make travel decisions. Public health administrators depend on test results to monitor the pandemic, while policymakers rely on this data to inform shutdown and reopening directives. Higher positivity rates indicate higher infection and community spread. It also gauges whether testing is keeping up with the rate of transmission. Fig. A3 in the Appendix shows that the daily positivity rate and COVID-19 cases are somewhat correlated. We see an increase in positivity rate as the first wave of COVID-19 cases kicks in. The second wave also witnesses an increase in positivity rate though the increase appears to be mild.

In Table 12, we report the findings when the positivity rate is used in lieu of COVID-19 cases. It is reassuring to see that these results concord with our original findings. A plausible explanation is that higher positivity rates mean higher community spread of the virus which leads to lockdowns. Lockdowns curb demand faster than capacity. The reduction in congestion ultimately improves OTP.

**Limitations of the study**

The trove of data generated during the COVID-19 pandemic has been unprecedented. This volume of data has been motivated, in part, by an impetus to gauge the harm caused by the pandemic as well as the development of policies to fight the virus. There are good reasons to...
believe that this endeavor will help prepare for the next pathogen. However, the poor coordination between the U.S. federal government and states has led to widespread COVID-19 statistics irregularities throughout the country. We discuss two well-known limitations of the COVID-19 data we used.

Testing
At the onset of the pandemic, COVID-19 tests appeared to be extremely limited, leaving individuals that were asymptomatic undetected (Armour et al., 2020). As testing access grew, its administration and reporting were inconsistent not only across states but also within states (Weaver and Ballhaus, 2020). Some reports indicate that for every recorded case of COVID-19, there are at least two unnoticed cases (Cash-Goldwasser et al., 2020). While some jurisdictions kept count only for antibody tests done in laboratories, others included antigen tests, known to be less-sensitive, in their test count even when these tests were conducted outside of laboratories.

Testing has also been patchy across U.S. states. For instance, some states designate “total tests” as the total count of unique individuals who had been tested, while for other states, this represents the total test count performed, including repeat testers. These differing methods have implications on how positivity rates are calculated.

Standardization
The Council of State and Territorial Epidemiologists notes that standardized infection monitoring is fundamental not only for consistent case identification and documentation but also for evaluating the potential burden of infection and for supporting public-health response efforts. Some jurisdictions release data on only confirmed cases, while others also include probable cases—a definition that has shifted over time (McGinty, 2020).

Table 9
Late-departing Flights Results, Market Fixed Effects Model.

|                          | (1)      | (2)      | (3)      | (4)      |
|--------------------------|----------|----------|----------|----------|
| In (Covid-19 cases)      | −0.2013***| −0.2005***| −0.2005***| −0.1966***|
|                          | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Carrier Characteristics  |          |          |          |          |
| Origin flight frequency  | 3.6281   | 3.2796   | 2.897    | 3.6333   |
|                          | (4.3955) | (4.3956) | (4.2957) | (4.3552) |
| Low-cost Carrier         | −0.0194***| −0.0270***| −0.0147**| −0.0230***|
|                          | (0.0060) | (0.0060) | (0.0059) | (0.0060) |
| Out of hub               | −0.0073***| −0.0081***| −0.0076***| −0.0079***|
|                          | (0.0064) | (0.0065) | (0.0063) | (0.0064) |
| Constant                 | −27.4506 | −24.4638 | −21.8839 | −27.5876 |
|                          | (35.6861)| (35.6871)| (34.8764)| (35.3594)|
| Market fixed effects     | x        | x        | x        | x        |
| Departure time block     |          |          |          |          |
| Arrival time block       |          |          |          |          |
| Day of month             |          |          | x        |          |
| Day of week              |          |          |          | x        |
| Observations             | 752,019  | 752,019  | 752,019  | 752,019  |
| R²                       | 0.32     | 0.32     | 0.35     | 0.33     |

Notes: The data are from the Airline On-Time Performance database, and we restrict the sample to the 55 most populous cities in the Continental United States. *p < 0.10; **p < 0.05; ***p < 0.01.

Source: U.S. Bureau of Transportation Statistics, U.S. Census Bureau, U.S. Centers for Disease Control and Prevention (CDC).
Table 10
COVID-19 Impacts on Arrival OTP via Load Factor.

|                      | Load Factor | Arrival Delay Minutes | Load Factor | Late-arriving flights |
|----------------------|-------------|-----------------------|-------------|-----------------------|
|                      | (1)         | (2)                   | (3)         | (4)                   |
| Load Factor          | 9.9385***   | 0.5753***             |             |                       |
| (Covid-19 Cases)     | (0.5449)    | (0.0391)              |             |                       |
| Flight Characteristics|             |                       |             |                       |
| Departure min late   | 0.8767***   |                       |             |                       |
| (0.0006)             |             |                       |             |                       |
| Late-departing flights|             |                       |             |                       |
|                      | 0.8018***   |                       |             |                       |
| (0.0011)             |             |                       |             |                       |
| Taxi out             | 0.0918***   |                       |             |                       |
| (0.0041)             |             |                       |             |                       |
| Taxi in              | 0.0045      |                       |             |                       |
| (0.0067)             |             |                       |             |                       |
| Carrier Characteristics|             |                       |             |                       |
| Origin flight frequency| 0.8747***   | −0.1204***            |             |                       |
| (0.0795)             | (0.0053)    |                       |             |                       |
| Low-cost Carrier     | 1.7648***   | −0.0977***            |             |                       |
| (0.0754)             | (0.0051)    |                       |             |                       |
| Into hub             | 0.8146***   | 0.0414***             |             |                       |
| (0.0696)             | (0.0047)    |                       |             |                       |
| Market Characteristics|             |                       |             |                       |
| Tourist destination  | 0.4568***   | −0.0954***            |             |                       |
| (0.1178)             | (0.0079)    |                       |             |                       |
| Competitive Market   | −0.0167***  | 0.0987***             |             |                       |
| (0.0632)             | (0.0043)    |                       |             |                       |
| Market size          | 0.1330**    | 0.0491***             |             |                       |
| (0.0579)             | (0.0040)    |                       |             |                       |
| Constant             | −15.9610*** | 0.0663                |             |                       |
| (0.9850)             | (0.0681)    |                       |             |                       |
| Observations         | 587,758     | 587,758               |             |                       |
| $R^2$                | 0.77        | 0.55                  |             |                       |

Notes: The data are from the Airline On-Time Performance database, and we restrict the sample to the 55 most populous cities in the Continental United States. *p < 0.10; **p < 0.05; ***p < 0.01. Source: U.S. Bureau of Transportation Statistics, U.S. Census Bureau, U.S. Centers for Disease Control and Prevention (CDC).

Table 11
COVID-19 Impacts on Departure OTP via Load Factor.

|                      | Load Factor | Departure Delay Minutes | Load Factor | Late-departing flights |
|----------------------|-------------|-------------------------|-------------|-----------------------|
|                      | (1)         | (2)                     | (3)         | (4)                   |
| Load Factor          | 15.4460***  | 10.694***               |             |                       |
| (8.1588)             | (0.0447)    |                       |             |                       |
| (Covid-19 Cases)     | −0.01716*** | −0.01716***             |             |                       |
| (5.26E-05)           | (5.26E-05)  |                       |             |                       |
| Carrier Characteristics|             |                       |             |                       |
| Origin flight frequency| −7.7634***  | −0.0516***             |             |                       |
| (0.1426)             | (0.0078)    |                       |             |                       |
| Low-cost Carrier     | −9.0099***  | 0.6174***              |             |                       |
| (0.1273)             | (0.0070)    |                       |             |                       |
| Out of hub           | −3.1114***  | 0.4970***              |             |                       |
| (0.1242)             | (0.0066)    |                       |             |                       |
| Market Characteristics|             |                       |             |                       |
| Tourist destination  | 1.9449***   | −0.3117***             |             |                       |
| (0.2000)             | (0.0110)    |                       |             |                       |
| Competitive Market   | 2.5057***   | 0.2852***              |             |                       |
| (0.1079)             | (0.0059)    |                       |             |                       |
| Market size          | 1.8644***   | 0.4253***              |             |                       |
| (0.0972)             | (0.0053)    |                       |             |                       |
| Slot-restricted origin airport | 3.6464*** | 0.8878***              |             |                       |
| (0.2623)             | (0.0144)    |                       |             |                       |
| Constant             | 68.3964***  | −9.2969***             |             |                       |
| (1.6988)             | (0.0930)    |                       |             |                       |
| Observations         | 751,869     | 751,869                |             |                       |
| $R^2$                | 0.01        | 0.01                   |             |                       |

Notes: The data are from the Airline On-Time Performance database, and we restrict the sample to the 55 most populous cities in the Continental United States. *p < 0.10; **p < 0.05; ***p < 0.01. Source: U.S. Bureau of Transportation Statistics, U.S. Census Bureau, U.S. Centers for Disease Control and Prevention (CDC).
case counts do not always depict the total number of infections as some individuals may be asymptomatic or mildly ill and not tested.

Retrospectively, examining the COVID-19 data sets—albeit imperfect—can help assess the effectiveness of past public health decisions and ameliorate future policy responses.

Conclusion

This paper examines the effects of COVID-19 on airline on-time performance. The paper contributes to the burgeoning set of papers that estimates the product quality impacts of the COVID-19 pandemic in the airline industry. Using high frequency (daily) data of reported cases of COVID-19 and OTP, and controlling for relevant factors that are likely to influence OTP, our analysis yields key findings. First, we find that reported COVID-19 cases are negatively associated with flight delays. More precisely, a standard deviation increase in COVID-19 cases reduces arrival delay by 1 min 42 s and departure delay by 2 min.

Second, we show that this negative relationship is true for both departure and arrival OTP and regardless of how OTP is measured. Third, we also show that these OTP effects of COVID-19 are robust to flight, carrier and market characteristics as well as market fixed effects specifications. Taken together, our results suggest that despite the economic fallout from the pandemic, a silver lining appears to be that flights are departing and arriving with less delay in greater numbers amid the pandemic.

As the pandemic continues to wreak havoc across industries, further investigation of the brass tacks of product quality implications of COVID-19 in the airline industry may bring forth invaluable insights. An avenue would be to adopt a machine learning approach and break the data into train and test sets. This would allow for a deeper look at the heterogeneity in our results.

Furthermore, as congestion has increased in recent years, major airlines have padded their schedules to more accurately reflect the longer gate-to-gate travel time caused by air traffic problems of all sorts. However, we found a puzzling fact that reported COVID-19 cases are negatively associated with flight delays. More precisely, a standard deviation increase in COVID-19 cases reduces arrival delay by 1 min 42 s and departure delay by 2 min.

Table 12

|                   | Arrival Delay Minutes | Late-arriving flights | Departure Delay Minutes | Late-departing flights |
|-------------------|-----------------------|-----------------------|-------------------------|-------------------------|
| Covid-19 positivity rate | −0.0695*** (0.0126)  | −0.0037*** (0.0008)  | 0.4256*** (0.0202)     | −0.0393*** (0.0006)     |
| Flight Characteristics |                       |                       |                         |                         |
| Departure min late | 0.8717*** (0.0007)    |                       |                         |                         |
| Late-departing flights | 0.7731*** (0.0014)   |                       |                         |                         |
| Taxi out | 0.1317*** (0.0047)    | 0.0300*** (0.0003)   |                         |                         |
| Taxi in | 0.0492*** (0.0071)    | 0.0281*** (0.0004)   |                         |                         |
| Carrier Characteristics |                   |                       |                         |                         |
| Origin flight frequency | 1.3048*** (0.0870)   | −0.0457*** (0.0053)  | −6.9571*** (0.1573)   | −6.9571*** (0.1573)    |
| Low-cost Carrier | 1.3929*** (0.0790)    | −0.1024*** (0.0048)  | −10.1010*** (0.1285)  | −10.1010*** (0.1285)  |
| Into hub | 0.6607*** (0.0061)    | 0.0326*** (0.0046)   |                         |                         |
| Out of hub |                         | −3.7291*** (0.1358)  | 0.0913*** (0.0040)    |                         |
| Market Characteristics |                   |                       |                         |                         |
| Tourist destination | 0.7413*** (0.1286)  | −0.0990*** (0.0079)  | 3.1147*** (0.2209)     | 0.2132*** (0.0065)     |
| Competitive Market | 0.0429 (0.0699) | 0.0756*** (0.0043)  | 2.6907*** (0.1220)     | 0.2817*** (0.0036)     |
| Market size | −0.2474*** (0.0641)  | 0.0146*** (0.0039)  | 1.6036*** (0.1113)     | 0.2513*** (0.0033)     |
| Slot-restricted origin airport |              |                         | 2.6978*** (0.3078)     | −0.2864*** (0.0091)   |
| Constant | −9.9574*** (1.0693)   | 0.2183*** (0.0656)   | 70.0317*** (1.9353)    | −5.1541*** (0.0571)   |
| Observations | 454,836               | 454,836               | 595,756                 | 595,756                 |
| $R^2$ | 0.79                  | 0.44                  | 0.02                    | 0.05                    |

Notes: The data are from the Airline On-Time Performance database, and we restrict the sample to the 55 most populous cities in the Continental United States. *p < 0.10; **p < 0.05; ***p < 0.01.

Source: U.S. Bureau of Transportation Statistics, U.S. Census Bureau, U.S. Centers for Disease Control and Prevention (CDC).

CRediT authorship contribution statement

Jules Yimga: Conceptualization, Methodology, Software, Data curation, Writing - original draft, Writing - review & editing.
Appendix

Fig. A1. Histogram of “minutes late”

Fig. A2. Late Flights as a Share of Total Flights

Fig. A3. Positivity Rate
### Table A1

Cities and airports.

| Rank | City, State | Airports | City, State | Airports |
|------|-------------|----------|-------------|----------|
| 1    | New York    | LGA, JFK, EWR | Las Vegas, NV | LAS |
| 2    | Los, Angeles, CA | LAX, BUR | Louisville, KY | SDF |
| 3    | Chicago, IL | ORD, MDW | Portland, OR | PDX |
| 4    | Dallas, TX | DAL, DFW | Oklahoma City, OK | OKC |
| 5    | Houston, TX | HOU, IAH, EFD | Tucson, AZ | TUS |
| 6    | Phoenix, AZ | PHX | Atlanta, GA | ATL |
| 7    | Philadelphia, PA | PHL | Albuquerque, NM | ABQ |
| 8    | San Antonio, TX | SAT | Kansas City, MO | MCI |
| 9    | San Diego, CA | SAN | Sacramento, CA | SMF |
| 10   | San Jose, CA | SJC | Long Beach, CA | LGB |
| 11   | Denver-Aurora, CO | DEN | Omaha, NE | OMA |
| 12   | Detroit, MI | DTW | Miami, FL | MIA |
| 13   | San Francisco, CA | SFO | Cleveland, OH | CLE |
| 14   | Jacksonville, FL | JAX | Oakland, CA | OAK |
| 15   | Indianapolis, IN | IND | Colorado Springs, CO | COS |
| 16   | Austin, TX | AUS | Tulsa, OK | TUL |
| 17   | Columbus, OH | CMH | Wichita, KS | ICT |
| 18   | Charlotte, NC | CLT | St. Louis, MO | STL |
| 19   | Memphis, TN | MEM | New Orleans, LA | MSY |
| 20   | Minneapolis-St. Paul, MN | MSP | Tampa, FL | TPA |
| 21   | Boston, MA | BOS | Santa Ana, CA | SNA |
| 22   | Baltimore, MD | BWI | Cincinnati, OH | CVG |
| 23   | Raleigh-Durham, NC | RDU | Pittsburg, PA | PIT |
| 24   | El Paso, TX | ELP | Lexington, KY | LEX |
| 25   | Seattle, WA | SEA | Buffalo, NY | BUF |
| 26   | Nashville, TN | BNA | Norfolk, VA | ORF |
| 27   | Milwaukee, WI | MKE | Ontario, CA | ONT |
| 28   | Washington, DC | DCA | IAD | IAD |

1. New York-Newark-Jersey.
2. Dallas-Arlington-Fort Worth-Plano, TX.
3. Phoenix-Temple-Mesa, AZ.

### Table A2

Average Arrival Delay Minutes, Destination Airport Ranking.

| Rank | Airport | Arrival Delay | Rank | Airport | Arrival Delay |
|------|---------|---------------|------|---------|---------------|
| 1    | DAL     | 20.4          | 22   | SEA     | 25.7          |
| 2    | OAK     | 20.8          | 23   | LGB     | 26.1          |
| 3    | HOU     | 21.1          | 24   | ABQ     | 26.4          |
| 4    | MDW     | 21.5          | 25   | MSY     | 26.4          |
| 5    | ONT     | 22.4          | 26   | MEM     | 26.4          |
| 6    | SAN     | 22.5          | 27   | TUS     | 26.6          |
| 7    | SJC     | 23.1          | 28   | ELP     | 26.8          |
| 8    | BWI     | 24.1          | 29   | MKE     | 26.9          |
| 9    | SNA     | 24.1          | 30   | DEN     | 27.0          |
| 10   | JAX     | 24.3          | 31   | CMH     | 27.0          |
| 11   | SMF     | 24.3          | 32   | OKC     | 27.1          |
| 12   | PDX     | 24.3          | 33   | CLE     | 27.2          |
| 13   | OMA     | 24.3          | 34   | ICT     | 27.2          |
| 14   | AUS     | 24.4          | 35   | IAS     | 27.5          |
| 15   | STL     | 24.5          | 36   | PHX     | 27.6          |
| 16   | SAT     | 24.7          | 37   | ATL     | 27.9          |
| 17   | BNA     | 24.7          | 38   | PIT     | 28.1          |
| 18   | BUR     | 25.1          | 39   | MSP     | 28.4          |
| 19   | MCI     | 25.3          | 40   | IND     | 28.5          |
| 20   | TUL     | 25.5          | 41   | BUF     | 29.2          |
| 21   | TPA     | 25.7          | 42   | SDF     | 29.4          |

Notes: Data do not include early arrivals.

### Table A3

Average Arrival Delay Minutes, Top 30 Airport Pairs.

| Rank | Airport Pair | Arrival Delay | Rank | Airport Pair | Arrival Delay |
|------|--------------|---------------|------|--------------|---------------|
| 1    | PHX - DEN    | 21.9          | 16   | LAX - JFK    | 29.3          |
| 2    | DEN - SEA    | 23.0          | 17   | LAX - SFO    | 29.4          |
| 3    | PHX - LAX    | 25.2          | 18   | DEN - LAX    | 30.0          |
| 4    | DEN - PHX    | 25.9          | 19   | DFW - LAX    | 30.0          |
| 5    | ATL - LGA    | 26.1          | 20   | ATL - ORD    | 30.2          |
| 6    | LAX - DEN    | 26.4          | 21   | DFW - ORD    | 31.2          |
| 7    | LAX - DFW    | 27.3          | 22   | DEN - LAS    | 32.0          |
| 8    | SEA - DEN    | 27.5          | 23   | ORD - ATL    | 32.1          |
| 9    | JFK - LAX    | 27.8          | 24   | ORD - DFW    | 32.2          |
| 10   | SEA - LAX    | 27.9          | 25   | SEA - SFO    | 32.6          |
| 11   | LGA - ATL    | 28.4          | 26   | LAS - LAX    | 33.9          |
| 12   | LAX - LAS    | 28.4          | 27   | ORD - LGA    | 34.4          |
| 13   | LAX - DEN    | 28.8          | 28   | SFO - SEA    | 34.7          |
| 14   | LAX - PHX    | 29.2          | 29   | SFO - LAX    | 36.2          |
| 15   | LAX - SEA    | 29.2          | 30   | LGA - ORD    | 38.9          |

Notes: Data do not include early arrivals.
Table A4
COVID-19 Impacts on the Share of Late Flights.

|                      | % Late-arriving Flights | % Late-departing Flights |
|----------------------|-------------------------|--------------------------|
| (COVID-19)           | (1)                     | (2)                      |
| In                   | −0.0028***              | −0.0037***               |
|                      | (0.0001)                | (0.0001)                 |
| Flight Characteristics|                         |                          |
| % Late-departing Flights | 0.7140***            |                          |
|                      | (0.0011)                |                          |
| Taxi out             | 0.0035***               |                          |
|                      | (2.75E-5)               |                          |
| Taxi in              | 0.0024***               |                          |
|                      | (4.28E-5)               |                          |
| Carrier Characteristics|                       |                          |
| Origin flight frequency | −0.0422***             | −0.0138***               |
|                      | (0.0005)                | (0.0006)                 |
| Low-cost Carrier     | −0.0194***              | 0.0323***                |
|                      | (0.0005)                | (0.0005)                 |
| Into hub             | −0.0145***              |                          |
|                      | (0.0005)                |                          |
| Out of hub           | −0.0011**               |                          |
|                      | (0.0005)                |                          |
| Market Characteristics|                       |                          |
| Tourist destination  | −0.0085***              | 0.0028***                |
|                      | (0.0008)                | (0.0008)                 |
| Competitive Market   | −0.0141***              | −0.0617***               |
|                      | (0.0004)                | (0.0004)                 |
| Market size          | −0.0172***              | −0.0257***               |
|                      | (0.0004)                | (0.0004)                 |
| Slot-restricted origin airport | −0.0156***         |                          |
|                      | (0.0010)                |                          |
| Constant             | 0.6548***               | 0.8276***                |
|                      | (0.0066)                | (0.0070)                 |
| Observations         | 587,898                 | 752,019                  |
| $R^2$                | 0.44                    | 0.05                     |

Notes: The data are from the Airline On-Time Performance database, and we restrict the sample to the 55 most populous cities in the Continental United States.  
*p < 0.10; **p < 0.05; ***p < 0.01. 
Source: U.S. Bureau of Transportation Statistics, U.S. Census Bureau, U.S. Centers for Disease Control and Prevention (CDC).

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