How does COVID-19 affect intertemporal price dispersion? Evidence from the airline industry

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Abstract

This study provides empirical evidence documenting how COVID-19 affects intertemporal price dispersion in the airline industry. Exploiting a unique panel of 43 million fares collected before and during the pandemic, we find that airlines discounted fares by an average of 57%. The rate of intertemporal price increases also declined, particularly in the last week to departure. We also find that flight-level price dispersion increased during the pandemic. Fare decreases (and the associated increase in price dispersion) are found to be driven primarily by the diffusion of COVID-19 at the destination as opposed to the origin market.

JEL classification: L11, L93, D40, I19.

Keywords: airlines, COVID-19, intertemporal pricing, price dispersion.

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1 Introduction

It is well-documented that deviations from the law of one price occur in a variety of retail markets. For example, instead of charging a single price for the same product, a distribution of prices often exists in the airline, automobile, book, gasoline, grocery, housing, insurance, mortgage, prescription drug, and wine markets (Allen et al., 2014; Borenstein and Rose, 1994; Cardebat et al., 2017; Chandra and Tappata, 2011; Clay et al., 2001; Dahlby and West, 1986; Gerardi and Shapiro, 2009; Goldberg and Verboven, 2001; Lewis, 2008; Li et al., 2013; MacDonald, 2000; Sorensen, 2000; Van Nieuwerburgh and Weill, 2010). Accordingly, a considerable empirical and theoretical literature has developed to better understand the principal determinants of this observed price dispersion (Barron et al., 2004; Burdett and Judd, 1983; Dana, 1999, 2001; Kaplan et al., 2019; McAfee, 1995; Pennerstorfer et al., 2020; Reinganum, 1979; Salop, 1977; Salop and Stiglitz, 1977, 1982; Shepard, 1991). We add to this literature by examining how intertemporal price dispersion in the airline industry is affected by the global economic slowdown caused by the COVID-19 pandemic.

Similar to Cornia et al. (2012), the focus of our study is the United States (U.S.) airline industry and how price dispersion is correlated with prevailing macroeconomic conditions.[1] In Cornia et al. (2012), price dispersion was found to move pro-cyclically with the business cycle (i.e., increasing during expansionary phases and decreasing during recessionary phases). Thus, one might expect airline price dispersion to fall during the economic slowdown caused by the COVID-19 pandemic. However, because each recession is unique, it is not abundantly clear that pro-cyclical behavior also extends to the COVID-19 recession.

In particular, the COVID-19 recession is unique in the aspect that adverse supply and demand shocks have permeated across a broad range of industries. Yet, few industries were as severely impacted as the airline industry. As governments imposed travel restrictions to

[1]Other studies that examine airline price dispersion include Borenstein and Rose (1994); Gaggero and Piga (2011); Gerardi and Shapiro (2009); Hayes and Ross (1998); Mantin and Koo (2009); Orlov (2011); Sengupta and Wiggins (2014).

curb COVID-19's spread, airlines were forced to cancel flights and the remaining flights that operated often flew half empty. The resulting drop in travel demand was more severe than other recent crises affecting the industry (e.g., the September 11th terrorist attack, 2003 SARS outbreak, 2008 financial crisis, or the 2009 swine flu pandemic).

To determine how COVID-19 affects intertemporal price dispersion, we exploit a unique panel of over 43 million fares collected over a twelve-month period. Flights in our sample depart between October 1st, 2019 and August 31st, 2020, providing us with over five months of data prior to COVID-19 being declared a national emergency in the U.S. and over five months of data during the national emergency.[2] Notably, because we track the price of each flight in the sixty-day period before departure, we are able to examine how new COVID-19 case counts at the origin and destination markets during a flight's booking period affect both prices and price dispersion.

We have five main findings. Foremost, as COVID-19 spread across the country, airlines responded by discounting fares by an average of 57%.[3] Second, although fares exhibit the typical pattern of increasing as the departure date approaches, the rate of intertemporal price hikes declined during the pandemic, especially in the last week to departure. Third, we find that an increase in new COVID-19 cases at the destination decreases fares while new cases at the origin has no statistically measurable effect. Fourth, we find that flight-level price dispersion *increased* during the pandemic. Fifth, we find that an increase in new COVID-19 cases at the destination increases price dispersion while new cases at the origin has no statistically measurable effect.

Although we find that pandemic fare decreases (and the associated increase in price dispersion) are driven primarily by the diffusion of COVID-19 at the destination instead of

[2]COVID-19 was declared a national emergency in the U.S. on March 13th, 2020. The first state to issue a statewide stay-at-home order was California on March 19th, 2020.

[3]Consistent with this finding, the Bureau of Transportation Statistics (BTS) recorded the lowest inflation-adjusted annual fare of $292 in 2020, down 19% from the previous low of $359 in 2019. See Release Number: BTS 27-21, available at `https://www.bts.gov/newsroom/average-air-fares-dropped-all-time-low-2020`.

the origin, we believe these findings are sensible from the passenger perspective. In particular, the origin typically represents where a prospective passenger resides. If new cases are high at home, people are likely not traveling, irrespective of the destination. In contrast, the destination is typically where the passenger leaves home to travel to. If the number of new COVID-19 cases at the destination are high, fares must be heavily discounted to entice prospective passengers to purchase when the risk of becoming infected at the destination is high.

The rest of this article is organized as follows. Section 2 describes the data sources used in the empirical analysis. Section 3 presents a descriptive analysis of the dynamics of airline pricing during the booking period. Section 4 describes the econometric model used to examine intertemporal pricing and presents intertemporal pricing results. Section 5 describes the econometric model used to examine price dispersion and presents price dispersion results. Finally, Section 6 provides concluding remarks.

2 Data

To examine how the COVID-19 pandemic affected intertemporal pricing and price dispersion in the U.S. airline industry, we rely on several data sources. However, the data underlying our main empirical results are obtained from two primary sources: fare and itinerary data from a major online travel agency (OTA) and COVID-19 case counts from the National Center for Health Statistics (NCHS). Section 2.1 describes the fare and itinerary data, Section 2.2 the data on the number of COVID-19 cases, and Section 2.3 the other data sources used for the construction of instrumental variables.

2.1 Fare and Itinerary Data

Previous studies that examine airline price dispersion typically rely on the U.S. Department of Transportation's Airline Origin and Destination Survey (DB1B).[4] These data are released quarterly and represent a 10% random sample of tickets purchased for domestic air travel. However, the DB1B does not include information on the specific flight(s) purchased or the exact purchase and departure dates. Thus, the DB1B are not appropriate for examining how fares for a given flight evolve over time nor can the data be used to control for key factors that may affect fares during the COVID-19 pandemic such as advance-purchase requirements or the number of COVID-19 cases at the origin and destination markets at the time of purchase. To overcome these shortcomings, we collected published fare and itinerary information from a major OTA.[5] Nevertheless, because the DB1B are transacted fares while data from an OTA are only published fares, we employ the DB1B for a robustness check in Section 5.2.1.

In lieu of collecting data for all possible routes in the U.S., DB1B data from the third and fourth quarters of 2018 were first used to identify the top directional airport-pair markets within the continental U.S. ranked by total passenger traffic.[6] 148 of these top directional airport-pairs were selected for analysis and include a mix of competitive, monopoly, duopoly, and connecting only (i.e., airport-pairs without nonstop service) markets. Figure 1 displays a map of the 148 markets included in our analysis. As the figure demonstrates, these routes provide fairly extensive coverage of the domestic U.S. market.

To construct our analysis sample, data were collected over a twelve-month period for flights departing between October 1$^{\text{st}}$, 2019 and August 31$^{\text{st}}$, 2020. Daily fare quotes were collected for one-way travel between each of the directional airport-pairs in Figure 1.[7] For

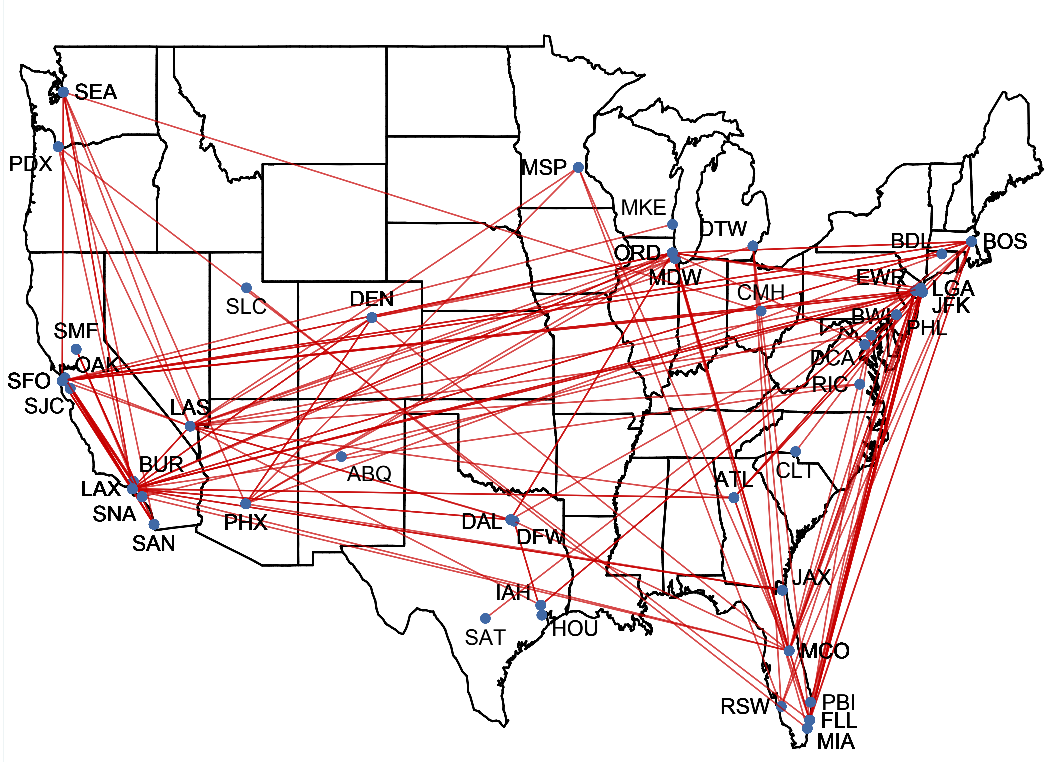
[4]For example, see Borenstein and Rose (1994), Gerardi and Shapiro (2009), and Cornia et al. (2012).

[5]Major OTAs include Expedia, Google Flights, and Kayak. Previous studies that analyze data from a major OTA include Escobari (2009), Escobari et al. (2019), Gaggero and Luttmann (2021), and Luttmann (2019), among others.

[6]A market in our analysis is defined as a directional airport-pair. Accordingly, Los Angeles (LAX)-Chicago (ORD) and Chicago (ORD)-Los Angeles (LAX) are treated as separate markets.

[7]Similar to Bilotkach et al. (2010), Escobari et al. (2019), Gaggero and Luttmann (2021), and Luttmann (2019), we focus on one-way trips due to difficulties in specifying trip duration. For any given departure date, there are a large number of roundtrip fares that could potentially be gathered, each depending on trip

Figure 1: U.S. domestic routes included in our analysis sample



each route, fares for each of the next sixty travel days were collected to capture leisure travelers who purchase flights well in advance of the departure date and business travelers who purchase flights closer to the date of departure. This data collection strategy also allows us to track the price of an individual flight (or pair of flights for connecting trips) over the sixty-day period prior to departure.

Our sampling procedure resulted in a unique sample of 43,160,581 observations. Roughly 35% of our observations are for connecting trips. The airlines included in our sample include four full-service carriers (Alaska, American, Delta, and United) and five low-cost carriers (Allegiant, Frontier, JetBlue, Spirit, and Sun Country).[8]

duration. For example, fares for two-day trips are likely different from seven or ten-day trips.

[8]Fare quotes for Southwest Airlines are not available on travel aggregator websites such as Expedia, Google Flights, and Kayak. However, the presence of Southwest is accounted for in our empirical analysis when we construct any variable controlling for the number of carriers or flights serving a given route.

2.2 COVID-19 Cases

From the NCHS, we downloaded the daily number of new COVID-19 cases for each state in the continental U.S.[9] These daily numbers were then used to construct seven-day moving average new COVID-19 case counts for each origin and destination market in our sample (see routes in Figure 1).

2.3 Other Data Sources

In general, measures of competition and flight frequency are endogenous in analyses of airline pricing. For example, markets with high fares may be attractive for new entrants. However, these markets may also be unattractive if high fares are the result of entry barriers such as slot controls or limited gate access at the endpoint airports. Accordingly, the potential simultaneity bias that results from an airline's decision to enter or exit a given route may bias results. To correct for this potential endogeneity, we employ an instrumental variables strategy (see Section 5.1).

To instrument for the level of competition on a given departure date, we construct lagged measures of competition using the U.S. Department of Transportation's Airline On-Time Performance Statistics database.[10] Furthermore, since jet fuel prices affect the marginal cost of serving a given route, we collect daily jet fuel prices from the U.S. Energy Information Administration to instrument for flight frequency.[11]

3 Descriptive Analysis

To provide preliminary evidence on the impact of COVID-19 on fares, Figure 2 displays the average fare per mile for nonstop flights across each booking date in our sample (i.e., *NOT*

[9]See `https://covid.cdc.gov/covid-data-tracker/`. Navigate to "Cases & Death" to select "Cases & Death by States" and then click on "View Historic Case and Death Data" to download the data.

[10]See `https://transtats.bts.gov/Fields.asp?gnoyr_VQ=FGK`.

[11]See `https://www.eia.gov/dnav/pet/hist/EER_EPJK_PF4_RGC_DPGD.htm`.

each *departure* date). The booking date is the date when the fare is observed and includes flights departing in the next few days as well as flights departing up to sixty days in the future. However, the proportion of flights departing in the next few days and the proportion of flights departing in the next sixty days are approximately equal across booking dates. Thus, pricing dynamics in Figure 2 are displayed over a time horizon of similar average length across booking dates.[12]

To relate the pricing decision of airlines to the diffusion of the COVID-19 pandemic, we calculated the average number of new COVID-19 cases across each state and calendar date in our sample. Then, to smooth any reporting differences, we computed the seven-day moving average number of new cases.[13] This moving average is displayed on the secondary Y-axis of Figure 2.

As demonstrated by Figure 2, there is clear evidence of an inverse relationship between the number of new COVID-19 cases and the average nonstop fare. For instance, in early March 2020, fares fell substantially as the pandemic began to spread in the United States. Then, as the number of new COVID-19 cases declined between May and June, average fares increased.

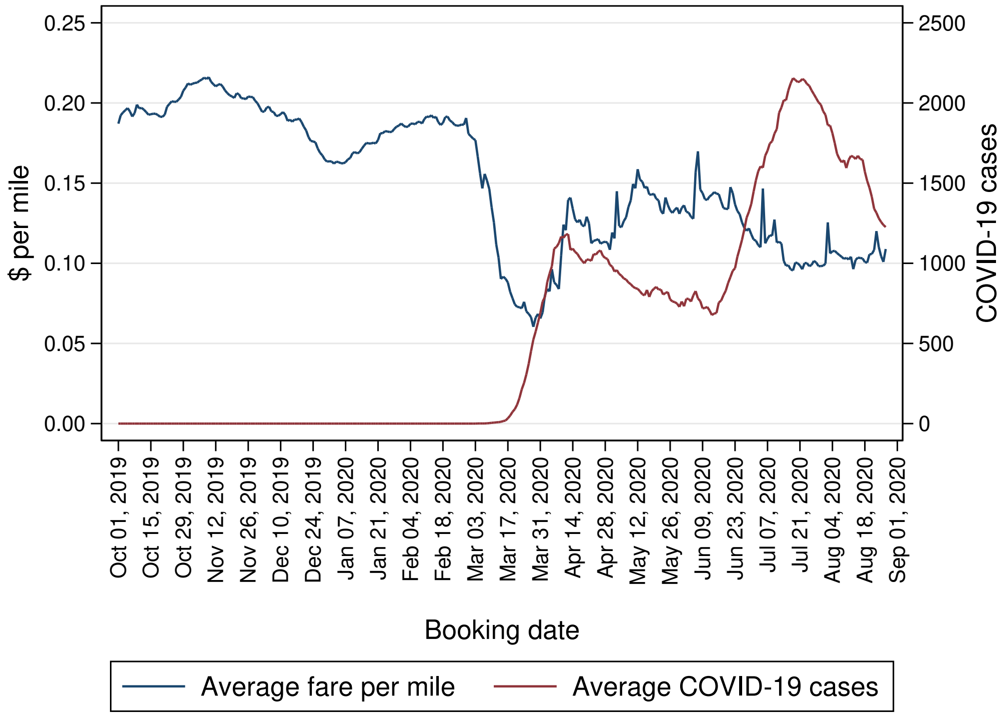
To further illustrate how the intertemporal behavior of fares evolved prior to and during the pandemic, Figure 3 displays the average nonstop fare per mile by number of days to departure for full-service carriers (FSCs) in Panel A and low-cost carriers (LCCs) in Panel B. Flights are grouped by month of departure to demonstrate the impact of COVID-19 on fares over time.

In general, fares are lower during the pandemic months of our sample (March through August). This result is particularly clear for FSCs (Panel A), but less evident for LCCs

[12] This balance is also maintained in the booking months of July and August since the latest departure date included in the construction of Figure 2 is October 26$^{\text{th}}$, 2020. For example, booking dates in August 2020 include flights that depart in August, September, and October 2020.

[13] The pattern of the seven-day moving average of new COVID-19 cases in our sample is similar to what is observed over the entire United States. For comparison, see `https://covid.cdc.gov/covid-data-tracker/#trends_dailytrendscases`.

Figure 2: Average nonstop fare per mile and average new COVID-19 cases by booking date



(Panel B). This finding is sensible considering that price-cost margins (i.e., markups) for LCCs are already low, suggesting that LCCs do not have substantial room to decrease fares in response to adverse demand shocks. In contrast, FSCs typically operate with higher price-cost margins, implying more leeway to decrease fares in response to an adverse demand shock. Furthermore, it is also likely that the pandemic more severely impacted routes with substantial business traffic (routes typically served by FSCs) than routes with high volumes of leisure traffic (routes typically served by LCCs). Since most differences in Figure 3 are observed for FSCs, the subsequent discussion primarily focuses on the intertemporal pricing behavior of FSCs. However, some of the following discussion also applies to LCCs.

Considering that our data collection window begins sixty days prior to a flight's departure, the March and April diagrams in Figure 3 include fares collected during the pre-pandemic period and fares collected during the outbreak of the pandemic. Although we suspect that the decline in average fares observed in April and the steep increase in the last week to

Figure 3: Average nonstop fare per mile by days to departure and month of departure

(a) Full-service carriers

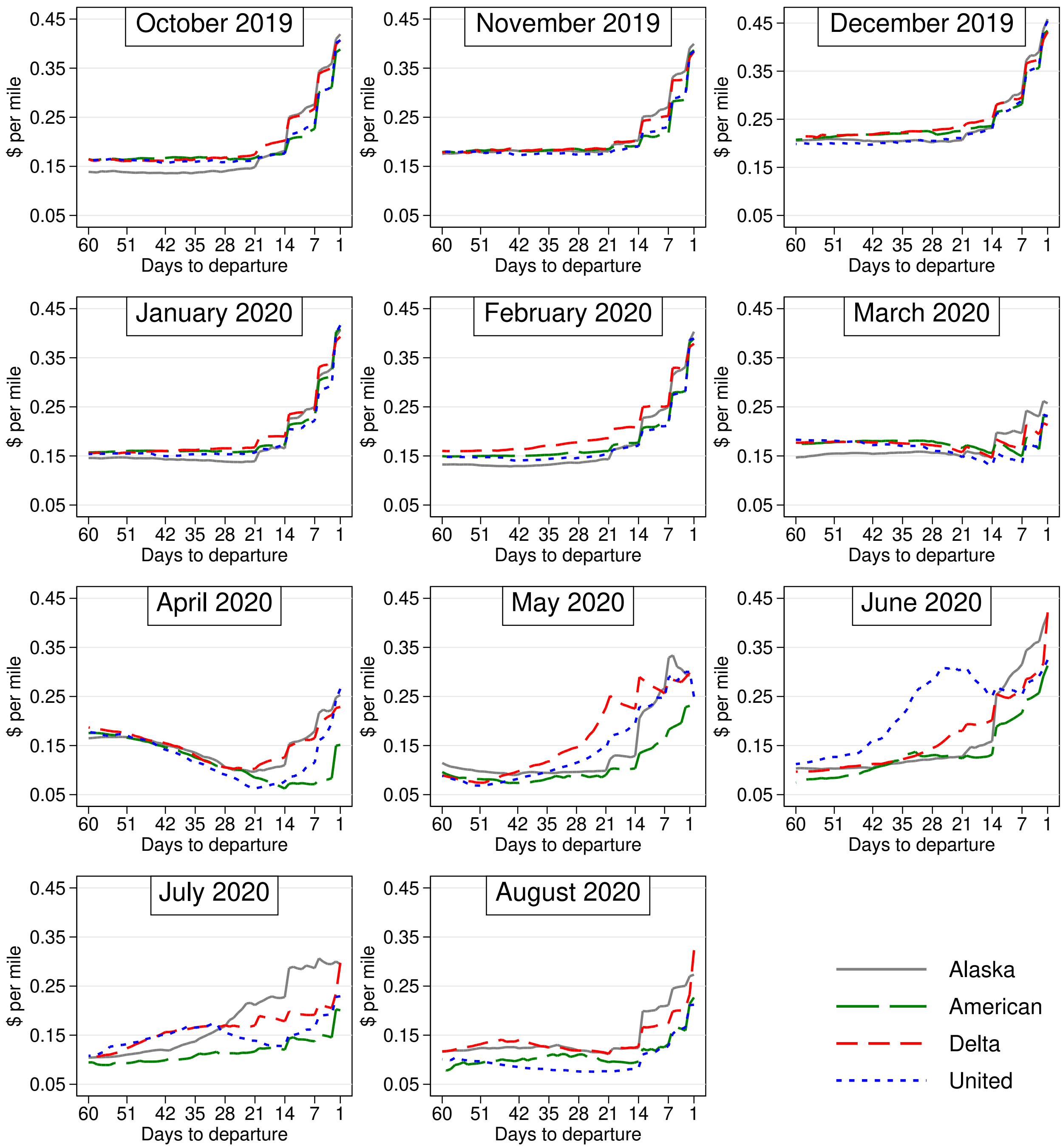
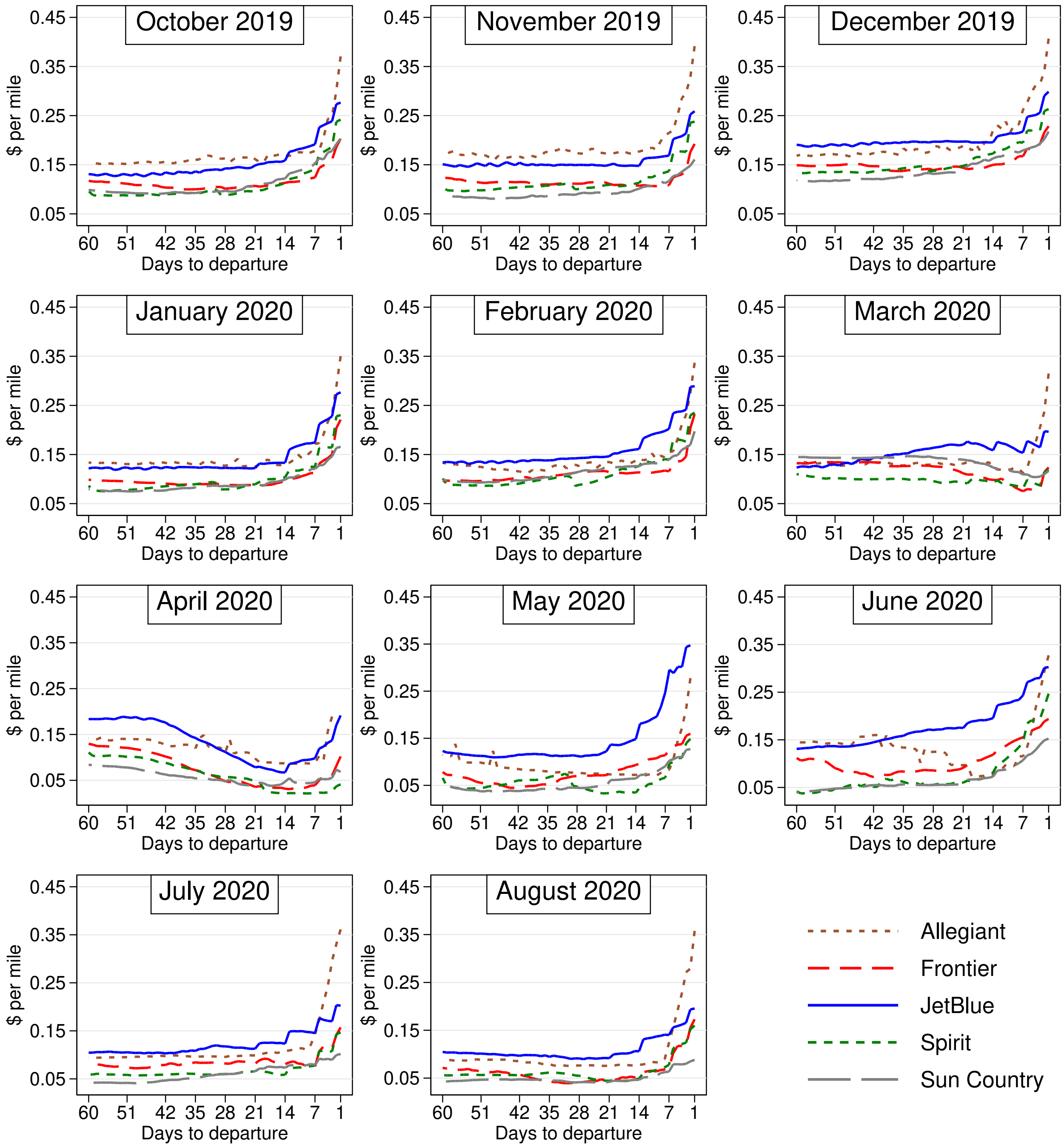


Figure 3: Average nonstop fare per mile by days to departure and month of departure (cont.)

(b) Low-cost carriers



departure observed in March were likely due to the pandemic, we cannot definitively state that these changes were solely due to COVID-19.[14]

All diagrams from May 2020 onwards in Figure 3 are fully affected by the pandemic. For FSCs, it is worth comparing the May, June, and July 2020 diagrams with those completely unaffected by COVID-19 (i.e., the October, November, and December 2019 diagrams). Two important regularities are observed in the fare diagrams for the last three months of 2019. Foremost, the average fare monotonically increases as the departure date approaches, with four well-defined fare hikes occurring from twenty-one to twenty, fourteen to thirteen, seven to six, and three to two days prior to departure.[15] Second, average fares across carriers mostly overlap, indicating that FSCs adopt very similar intertemporal pricing strategies on average.

In contrast, these regularities are not observed in the May, June, and July 2020 diagrams for FSCs. In these months, the increasing trend in fares across carriers are not monotonic and the average fare curves do not overlap in the same manner as the 2019 diagrams. For instance, the irregular pricing curves for United and Alaska in July and the irregular pricing curve for Delta in May 2020 suggest that each FSC employed differential pricing responses during the first few months of the COVID-19 pandemic. This type of behavior is expected to occur if yield management staff for each FSC had to manually intervene in the process of updating fares, ignoring the output suggested by pricing algorithms that were not accustomed to dealing with the drastic drop in demand induced by the diffusion of COVID-19. A similar argument may apply to some LCCs.

Finally, the regularities observed during the pre-pandemic months reappear in August 2020 with well-defined fare hikes observed from fourteen to thirteen, seven to six, and three to two days prior to departure. However, the average fare remains lower than during the

[14]Since COVID-19 was not declared a national emergency in the U.S. until March 13$^{\text{th}}$, 2020 and the first statewide stay-at-home order was not issued until March 19$^{\text{th}}$, 2020, the majority of observations within one week of departure in the March diagrams were collected during the pre-pandemic period.

[15]As discussed in Gaggero and Luttmann (2021), these fare hikes likely reflect the expiration of discount fare classes attached to the three-week, two-week, one-week, and three-day advance purchase requirements.

pre-pandemic period for both FSCs and LCCs.

4 COVID-19 and Intertemporal Pricing

4.1 Econometric Model of Intertemporal Pricing

To identify how intertemporal pricing changed during the COVID-19 pandemic, we estimate equation (1),

$$
\begin{aligned}
\log(Fare_{rafdb}) \;=\; & \mu + \sum_{i=1}^{4}\delta_i \cdot DaysToDeparture_{ib} + \gamma \cdot CovidOutbreak_b \\
& + \sum_{i=1}^{4}\gamma_i \cdot CovidOutbreak_b \times DaysToDeparture_{ib} \\
& + \alpha \cdot CovidOrigin_{rafdb} + \beta \cdot CovidDest_{rafdb} + \rho_{raf} + \varepsilon_{rafdb} \qquad (1)
\end{aligned}
$$

where the individual dimension of the panel is the combination of route (i.e., directional airport-pair) r, airline a, and flight f that is scheduled to depart on a given day d.[16] The time dimension of the panel is represented by b, which records the day the fare is observed (i.e., the day the fare is booked).

In this specification, the fixed-effect ρ identifies the unique combination of flight, airline, route, and departure date. Since airline and route are specific to each f, we refer to ρ as the set of flight-date fixed-effects. Notably, because the departure date is time-invariant within each f, any fare effect attributable to the time-of-day, day-of-week, or month-of-departure is absorbed by ρ. A similar argument applies to the level of competition, which is also date-specific, and therefore time-invariant within the panel. Accordingly, these flight-date fixed effects control for any time-invariant flight, airline, and route-specific characteristics that

[16] For example, the American Airlines flight from Chicago (ORD) to Los Angeles (LAX) on April 22$^{\text{nd}}$, 2020 that departs at 7:23am is an example of f. By extension, a combination of flights on the same itinerary is another example of f. For instance, the pair of Delta flights on November 15$^{\text{th}}$, 2019 from Chicago (MDW) to Atlanta (ATL) and from Atlanta (ATL) to Las Vegas (LAS) is another example of f.

affect fares.[17]

The first term of the right hand side of equation (1) are the set of days to departure dummies, which allow fares to change as the departure date approaches in a nonlinear way. As suggested by Figure 3 and the analysis in Gaggero and Luttmann (2021), we split the booking period into five mutually exclusive groups: 60 to 21, 20 to 14, 13 to 7, 6 to 3, and 1-2 days before departure. The earliest days-to-departure group (60 to 21 days) is excluded, so that the coefficients on the included $DaysToDeparture$ dummies indicate the change in fare relative to this earliest booking period.

The effect of the COVID-19 pandemic on fares is accounted for by *CovidOutbreak*, *CovidOrigin*, and *CovidDest*. *CovidOutbreak* is a dummy equal to one if the fare is collected on any day after March 13$^{\text{th}}$, 2020, the date when COVID-19 was declared a national emergency in the United States. *CovidOrigin* is the geometric mean (in thousands) of the 7-day moving average of new positive COVID-19 cases in the state of the origin airport. Similarly, *CovidDest* is the geometric mean (in thousands) of the 7-day moving average of new positive COVID-19 cases in the state of the destination airport. We use the 7-day moving average to reduce the impact of possible reporting differences across states, as well as to allow for possible spillover effects of nearby booking dates on fares.

The variables of interest in equation (1) are the set of interactions between *CovidOutbreak* and $DaysToDeparture$. Compared to the pre-pandemic period (i.e., before March 13$^{\text{th}}$, 2020), the coefficients on these interactions indicate how the rate of intertemporal price hikes changed during the pandemic for flight's booked 1-2, 3-6, 7-13, and 14-20 days prior to departure.

Finally, μ is the regression intercept and ε is the error term. We estimate the fixed effects model described by equation (1) using ordinary least squares (OLS) with standard errors

[17]For example, time-invariant flight-specific characteristics include the type of aircraft used and the scheduled departure and arrival times. Time-invariant carrier-specific characteristics include any fare effects attributable to the airline's frequent flyer program or average quality of service. In addition to the level of competition, other time-invariant route-specific characteristics include the level of airport dominance at the origin and destination airports, the route distance, and whether low-cost carriers are present on the route.

that are clustered at the route-level to allow for the residuals of flights operated by the same airline and other airlines on a given route to be correlated.

4.2 Intertemporal Pricing Results

Table 1 presents results from estimating the model described by equation (1). All specifications include flight-date fixed effects to control for any time-invariant flight, carrier, and route-specific characteristics that affect fares. The first column includes only the $DaysToDeparture$ dummies and confirms the well-documented empirical result that fares increase as the flight's departure date approaches, irrespective of the pandemic.[18] For example, the coefficient of 0.679 on *DaysToDeparture 1-2* indicates that flights booked in the last two days before departure are, on average, almost twice the price of comparable flights booked 21 to 60 days before departure (the omitted $DaysToDeparture$ group).[19]

To provide a baseline for how fare levels differ across the pre-pandemic and pandemic periods of our sample, column 2 adds the *CovidOutbreak* dummy to the specification presented in column 1. Notably, the R^2 almost doubles, illustrating the importance of *CovidOutbreak* for explaining pandemic fares. In particular, the coefficient of -0.835 on *CovidOutbreak* indicates that domestic fares in the six month period after COVID-19 was declared a national emergency were, on average, 57% cheaper than comparable fares prior to the emergency.

Column 3 adds the set of interactions between *CovidOutbreak* and the $DaysToDeparture$ dummies to the specification presented in column 2. Consistent with column 2, the positive coefficients on the $DaysToDeparture$ dummies indicate that fares increase as the departure date approaches while the negative coefficient on *CovidOutbreak* indicates that fares declined after Covid-19 was declared a national emergency. However, the negative coefficients on the four interaction terms indicate that the rate of intertemporal fare hikes during the pandemic

[18] For example, see Alderighi et al. (2015a,b); Bergantino and Capozza (2015); Escobari (2012, 2014); Escobari and Jindapon (2014); Gaggero and Piga (2010); Gaggero and Luttmann (2021), among others.

[19] Because the dependent variable is logged and *DaysToDeparture 1-2* is an indicator variable, the marginal effect is $100(e^{0.679} - 1) = 97.2\%$.

Table 1: Intertemporal pricing results

Dependent variable:	(1) ln(Fare)	(2) ln(Fare)	(3) ln(Fare)	(4) ln(Fare)
DaysToDeparture 1-2	0.679***	0.756***	0.806***	0.806***
	(0.019)	(0.019)	(0.023)	(0.023)
DaysToDeparture 3-6	0.444***	0.517***	0.543***	0.543***
	(0.024)	(0.022)	(0.027)	(0.027)
DaysToDeparture 7-13	0.216***	0.275***	0.274***	0.274***
	(0.020)	(0.018)	(0.020)	(0.020)
DaysToDeparture 14-20	0.021***	0.067***	0.073***	0.073***
	(0.008)	(0.007)	(0.007)	(0.007)
CovidOutbreak		-0.835***	-0.814***	-0.814***
		(0.029)	(0.031)	(0.031)
CovidOutbreak × DaysToDeparture 1-2			-0.156***	-0.137***
			(0.021)	(0.022)
CovidOutbreak × DaysToDeparture 3-6			-0.086***	-0.069***
			(0.024)	(0.024)
CovidOutbreak × DaysToDeparture 7-13			-0.007	0.008
			(0.016)	(0.015)
CovidOutbreak × DaysToDeparture 14-20			-0.025***	-0.013*
			(0.008)	(0.008)
CovidOrigin				-0.002
				(0.005)
CovidDestination				-0.019***
				(0.004)
R^2	0.171	0.300	0.302	0.303
Observations	43,160,581	43,160,581	43,160,581	43,160,581

Notes: Summary statistics are provided in Appendix Table A1. Marginal effects are interpreted as the $100(e^{\beta}$-$1)\%$ change in fare. All specifications include flight-date fixed effects that control for any time-invariant flight, carrier, and route-specific characteristics that affect fares. Standard errors are clustered at the route-level. Constant is included but not reported. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

are *lower* relative to the pre-pandemic period. In particular, the slowdown of intertemporal fare hikes during the pandemic is especially evident in the last week to departure. As previously illustrated in Figure 3b, this result may be driven by low-cost carriers who did not substantially increase fares in the last week to departure during the pandemic months of our sample.

Nevertheless, the statistically insignificant, albeit negative, coefficient on *CovidOutbreak*

$\times$ *DaysToDeparture 7-13* suggests that the slower rate of intertemporal fare hikes observed during the pandemic is not ubiquitous across days to departure groups. This finding is consistent with the fare hikes observed 7-13 days before departure in Figure 3a for full-service carriers during the pandemic months (e.g., Alaska in May-August or American and Delta in June).

To examine how heterogeneity in the diffusion of COVID-19 affects fares, column 4 adds the 7-day moving average number of new positive COVID-19 cases in the origin ($CovidOrigin$) and destination ($CovidDest$) states to the specification presented in column 3. The coefficients on $CovidOrigin$ and $CovidDest$ are both negative, providing additional evidence that COVID-19 adversely affected fares. However, the statistical insignificance and lower absolute magnitude of the $CovidOrigin$ coefficient implies that pandemic fare decreases are mainly driven by the diffusion of COVID-19 at the destination.

From the passenger perspective, this result is sensible. In particular, the origin typically represents where the passenger lives. If new cases are high at home, people are likely not traveling, irrespective of the destination. Accordingly, the impact of new COVID-19 cases at home is expected to be negative and not specific to a particular route. In contrast, the destination is typically where the passenger leaves home to travel to. If the number of new COVID-19 cases at the destination are high, fares must be lower to entice prospective passengers to purchase when the risk of becoming infected at the destination is high. The coefficient on $CovidDest$ provides an estimate of this effect: an increase of 1,000 new COVID-19 cases in the state of the destination airport is associated with a 1.9% fare decrease.

5 COVID-19 and Price Dispersion

Figure 3 illustrated a different pattern of airfares across the pre-pandemic and pandemic months of our sample. In the last quarter of 2019, when "COVID-19" was practically unknown, the diagrams are very similar across months and carriers: they unambiguously show that average fares increase as the departure date approaches with fare hikes that occur at specific days to departure (e.g., at three-week, two-week, one-week, and three-day milestones). The diagrams also show that the fare curves of FSCs substantially overlap with one another.

These regularities are not observed in the months following the outbreak of the pandemic. For example, in the second quarter of 2020, the fare curves are more distant from one another and huge price drops occur, suggesting that price dispersion may have increased during the pandemic months of our sample.

In this section, we examine how the pandemic affected flight-level price dispersion. The topic of price dispersion has spurred a considerable empirical literature. For example, previous studies have focused on how airline price dispersion is related to competition (Borenstein and Rose, 1994; Dai et al., 2014; Gaggero and Piga, 2011; Gerardi and Shapiro, 2009), capacity (Dana, 1999), demand characteristics (Mantin and Koo, 2009), and business cycles (Cornia et al., 2012). The analysis in this section enriches this literature by linking price dispersion to COVID-19.

5.1 Econometric Model of Price Dispersion

Following Borenstein and Rose (1994) and Gerardi and Shapiro (2009), we measure price dispersion with the Gini coefficient of inequality. Specifically, we estimate equation (2),

$$\begin{aligned} Gini^{lodd}_{rafd} \quad = \quad & \phi \cdot Carriers_{rd} + \theta \cdot Flights_{rd} + \sigma \cdot Holiday_d + \delta \cdot Weekend_d + \sum_{i=1}^{10} \mu_i \cdot Month_{id} + \\ & + \gamma \cdot CovidOutbreakBook_d + \alpha \cdot CovidOriginBook_{rd} + \\ & + \beta \cdot CovidDestBook_{rd} + \lambda_{raf} + \nu_{rafd} \end{aligned} \tag{2}$$

where the dependent variable $Gini^{lodd}$ is the Gini log-odds ratio, $ln[Gini/(1 - Gini)]$, which is employed to unbound the inequality index.[20] The Gini coefficient is computed using all

[20]By unbounding the inequality index, we are able to estimate equation (2) using a linear estimator such as OLS or two-stage least squares.

fares collected during the sixty-day booking period of each flight f.[21]

Similar to equation (1), r refers to the route, a the airline, and f the flight; the combination raf identifies the individual component of the panel. The time dimension of the panel is now d, the date-of-departure for flight f. In this specification, we refer to λ as the set of flight-number fixed effects (i.e., flights across multiple departure dates that have the same flight number, time-of-departure, and operating carrier). Since an observation in this analysis is the price dispersion of an individual flight, these flight-number fixed effects control for any flight-invariant characteristics that do not differ across departure dates (e.g., flight distance, operating carrier, and time-of-departure). In this respect, λ differs from ρ, the fixed-effect in equation (1), which identified an individual flight *and* departure date combination. For this reason, equation (2) includes more controls than equation (1).

In particular, equation (2) now includes flight-specific and route-specific controls that were time-invariant within the panel definition of equation (1). To control for the effect that competition has on price dispersion, $Carriers$ counts the number of nonstop carriers serving the route on the flight's date-of-departure. To proxy for the density of the route, $Flights$ counts the number of nonstop flights serving the route on the flight's date-of-departure (Gerardi and Shapiro, 2009). In our analysis, $Carriers$ and $Flights$ are computed on a daily basis, while previous studies relying on DB1B data use a monthly or quarterly aggregation.

Due to the possible simultaneity of price and quantity, $Carriers$ and $Flights$ are treated as endogenous variables and equation (2) is estimated using two-stage least squares (2SLS). We correct for this potential endogeneity using four instruments: (i) the number of nonstop carriers serving the route on the same corresponding day during the previous year,[22] (ii)

[21] Because several fights were canceled during the pandemic, the average number of fare observations for each f is 44. We restrict the calculation of the Gini coefficient to f's with at least 10 observations, since this threshold reduces potential small sample bias (Deltas, 2003). Note that this sample restriction is innocuous if applied to equation (1), whose results remain qualitatively unchanged when the restriction is implemented. These estimates are not reported in this paper, but are available from the authors upon request.

[22] By "same corresponding day" we mean that observations are matched with respect to the same day-of-week, although this may be a different calendar date across years. For example, the number of competitors serving a given route on Tuesday October 1$^{\text{st}}$, 2019 are paired with the number of competitors that served that same route on Tuesday October 2$^{\text{nd}}$, 2018.

the number of nonstop flights serving the route on the same corresponding day during the previous year, (iii) the daily jet fuel price,[23] and (iv) the interaction of the daily jet fuel price with flight distance. The first two instruments reflect that lagged market structure is correlated with current market structure.[24] The last two instruments reflect that jet fuel prices affect the marginal cost of serving a given route.

To control for flight-specific characteristics, we use a series of indicator variables. $Holiday$ is an indicator equal to one if the departure date of flight f falls on a holiday.[25] We expect lower fare dispersion on holidays due to peak-load pricing (Gaggero and Piga, 2011). $Weekend$ is an indicator equal to one if flight f departs on a Saturday or Sunday. Finally, $Month$ is the set of month-of-departure indicators that control for any possible seasonal variation in price dispersion.

The variables of interest in equation (2) are those that capture the effect of the pandemic on price dispersion: $CovidOutbreakBook$, $CovidOriginBook$, and $CovidDestBook$. $CovidOutbreakBook$ is set equal to the share of fare observations collected after March 13$^{\text{th}}$, 2020 that are used to calculate the Gini coefficient for flight f. This variable equals zero for all flights departing before March 13$^{\text{th}}$, 2020, since no fares were collected during the pandemic period (i.e., after COVID-19 was declared a national emergency in the U.S.). Since our fare collection begins sixty days prior to each flight's departure, this variable is positive, but smaller than one, for flights departing between March 13$^{\text{th}}$, 2020 and May 12$^{\text{th}}$, 2020 (i.e., fare observations are collected before and after the declaration of the national emergency). Finally, $CovidOutbreakBook$ equals one for any flight departing on or after May 13$^{\text{th}}$, 2020

[23] The daily jet fuel price is matched to the day that the flight is scheduled to depart. If the flight departs on a Saturday, Sunday, or holiday when financial markets are closed, we used the nearest previously available quote.

[24] Although unobserved cost and demand shocks may persist over time, these shocks are less likely to be correlated with previous year market structure than with current year market structure. Other papers that instrument for market structure using lagged measures include Davis (2005), Evans et al. (1993), Greenfield (2014), and Whalen (2007).

[25] Twelve holidays occur during our sample period: Columbus Day, Veterans Day, Thanksgiving, the day after Thanksgiving (i.e., Black Friday), Christmas Eve, Christmas Day, New Year's Eve, New Year's Day, Martin Luther King Jr. Day, Presidents' Day, Memorial Day, and Independence Day.

(i.e., all fare observations are collected after the declaration of the national emergency).[26]

To account for the spread of COVID-19 at the origin and destination, *CovidOriginBook* and *CovidDestBook* are set equal to the average number of new COVID-19 cases across the sixty-day booking period in the state of flight f's origin and the state of flight f's destination, respectively. Similar to *CovidOrigin* and *CovidDest* in equation (1), these variables test whether the pandemic's effect on price dispersion is predominantly driven by the spread of COVID-19 at one route endpoint over another.

5.2 Price Dispersion Results

The results of estimating equation (2) with flight-number fixed effects are provided in Table 2. The first two columns are specifications closest to those reported in Gerardi and Shapiro (2009) and Gaggero and Piga (2011). Column (1) reports OLS estimates while column (2) reports 2SLS estimates.

The sign on *Carriers* is negative, suggesting that an increase in competition decreases price dispersion. This finding is consistent with the results in Gerardi and Shapiro (2009) who found that an increase in the number of competitors reduces the higher percentiles of the fare distribution to a greater extent than the lower percentiles, thereby resulting in lower price dispersion. A negative relationship between competition and price dispersion is also found in Dai et al. (2014) and in Gaggero and Piga (2011).

Also consistent with Gerardi and Shapiro (2009) is the negative and statistically significant coefficient on *Flights*. Accordingly, denser routes (as measured by flight volumes) exhibit lower price dispersion. These are routes where, because of the large volume of passengers, it may be more difficult to distinguish passengers by their willingness-to-pay (i.e., more difficult to price discriminate), which translates to lower price dispersion.

The negative and statistically significant coefficient on *Holiday* is consistent with the

[26] *CovidOutbreakBook* corresponds to *CovidOutbreak* in equation (1). Over the sixty-day booking period, *CovidOutbreak* captures the overall effect of the pandemic on intertemporal pricing while *CovidOutbreakBook* captures the overall effect of the pandemic on price dispersion.

Table 2: Price dispersion results

	(1)	(2)	(3)
Dependent variable:	$Gini^{lodd}$	$Gini^{lodd}$	$Gini^{lodd}$
Estimator:	FE-OLS	FE-2SLS	FE-2SLS
Carriers	-0.018*	-0.053	-0.056*
	(0.010)	(0.033)	(0.032)
Flights	-0.005***	-0.007**	-0.007**
	(0.001)	(0.003)	(0.003)
Holiday	-0.059***	-0.062***	-0.063***
	(0.012)	(0.012)	(0.012)
Weekend	-0.027***	-0.029***	-0.029***
	(0.005)	(0.007)	(0.007)
CovidOutbreakBook			0.242***
			(0.064)
CovidOriginBook			-0.013
			(0.013)
CovidDestBook			0.024**
			(0.010)
R^2	0.015	0.015	0.017
Observations	937,636	936,241	936,241
Kleibergen-Paap rk LM statistic		22.962***	22.898***

Notes: Summary statistics are provided in Appendix Table A1. All specifications include flight-number fixed effects that control for any flight-invariant characteristics that do not differ across departure dates (e.g., distance, operating carrier, and time-of-departure). Constant and month-of-departure dummies are included but not reported. Standard errors are clustered at the route-level. In columns (2) and (3), *Carriers* and *Flights* are treated as endogenous variables and instrumented for using past-year values of *Carriers* and *Flights* in addition to the jet fuel price and the interaction between jet fuel price and flight distance. The null hypothesis of the Kleibergen-Paap rk LM statistic is that the equation is underidentified. First-stage estimates are reported in Appendix Table A2. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

results in Gaggero and Piga (2011), who find lower levels of price dispersion for flights departing during holiday periods. Due to peak-load pricing, fares are higher and less dispersed during the entire booking period for these holiday flights. Notably, the data in Gaggero and Piga (2011) cover a sample of European routes, while our present work is, to the best of our knowledge, the first to document the holiday effect on price dispersion for the U.S. domestic market.

Finally, the negative and statistically significant coefficient on $Weekend$ indicates lower price dispersion for flights departing on a Saturday or Sunday. This result likely reflects a more homogeneous mix of passengers on weekends relative to weekdays. Since business travelers seldom travel on weekends, most passengers traveling on Saturdays and Sundays are leisure travelers. The lack of weekend business travel limits an airline's ability to price discriminate, which translates to lower price dispersion (Gaggero and Piga, 2011).

Column (3) of Table 2 is new to the price dispersion literature and presents the impact of COVID-19 on price dispersion. The positive and statistically significant coefficient on *CovidOutbreakBook* indicates that fares collected during the pandemic period exhibit *more* price dispersion than similar fares collected before the pandemic.

Consistent with Table 1 where it was found that the number of new COVID-19 cases at the origin is not a significant factor affecting intertemporal pricing dynamics, the coefficient on *CovidOriginBook* in column (3) of Table 2 is also statistically insignificant. Therefore, new Covid-19 cases at the origin during the flight's booking period are not an important determinant of price dispersion. In contrast, the positive and statistically significant coefficient on *CovidDestBook* indicates that more COVID-19 cases at the destination during the flight's booking period results in higher levels of price dispersion.

5.2.1 Robustness: Price dispersion with DB1B fares

The analysis presented in Table 2 relied on published fares. Since there exists uncertainty regarding whether these fares were actually purchased at the published rates, we further relate our work to the existing empirical literature (Dai et al., 2014; Gerardi and Shapiro, 2009) by performing a robustness check using DB1B data. As discussed in Section 2.1, the DB1B are released quarterly and represent a 10% random sample of tickets purchased for domestic air travel. However, because the DB1B does not provide information on the purchase date (only the quarter of travel is reported), it is impossible to determine whether fares for a flight operated during the pandemic were purchased before or after the pandemic's outbreak. For example, a passenger flying in April 2020 could have booked the flight in December 2019, before the outbreak, or in late March 2020, after COVID-19 was declared a national emergency.

For this reason, we believe analyses relying on DB1B data will not be as accurate as our investigation with published fares in Table 2. Nevertheless, to minimize uncertainty associated with the timing of ticket purchases in the DB1B, we exclude the first quarter of 2020 because it mixes pre-pandemic and pandemic flights. We also exclude the second quarter of 2020 because, although it is entirely during the pandemic, a large volume of tickets may have been purchased before the pandemic's outbreak. Thus, to approximately capture the same time period as our published fare analysis, we employ two quarters of DB1B data: the last quarter of 2019 and the third quarter of 2020. The former quarter is clearly representative of the pre-pandemic period while the latter quarter is assumed to include tickets that are only purchased after the pandemic's outbreak.[27]

To comply with the aggregation of the DB1B, which are at the route, airline, and quarter level, we compute the Gini coefficient for price dispersion by route, airline, and quarter.[28] Accordingly, our estimating equation becomes,

$$\begin{aligned} Gini_{raq}^{lodd} &= \psi \cdot CovidOriginQuarter_{rq} + \omega \cdot CovidDestQuarter_{rq} + \\ &\quad \mu \cdot 2020Q3_q + \gamma \cdot Carriers_{rq} + \theta \cdot Flights_{rq} + \pi_{ra} + \varphi_{raq} \end{aligned} \tag{3}$$

where the individual component of the panel is the combination of route r and airline a, while the time dimension of the panel is represented by quarter q.

The definition of *Carriers* and *Flights* is similar to those in equation (2), except that these variables now vary by route and quarter rather than by flight and departure date.[29]

[27]It is possible that some DB1B fares from the third quarter of 2020 were booked during the pre-pandemic period. However, the number of these fares should be negligible since they reflect tickets that are purchased four or more months in advance.

[28]Consistent with Gerardi and Shapiro (2009), we exclude fares less than $20 from the calculation of the Gini coefficient since these fares are likely heavily discounted frequent flyer tickets.

[29]*Carriers* and *Flights* are constructed using the U.S. Department of Transportation's Airline On-Time Performance Statistics database. This database contains information on each individual domestic flight operated by U.S. carriers (e.g., the date and actual departure and arrival times). To generate quarterly averages, daily values of *Carriers* and *Flights* are averaged across each quarter.

Consistent with equation (2), $Carriers$ and $Flights$ are treated as endogenous variables and are instrumented for using their past-year values in addition to the interaction between the average quarterly jet fuel price and route distance.

$2020Q3$ is an indicator equal to one for the third quarter of 2020. $CovidOriginQuarter$ is the average number of new daily COVID-19 cases (in thousands) in the state of route r's origin during quarter q. Similarly, $CovidDestQuarter$ is the average number of new daily COVID-19 cases (in thousands) in the state of route r's destination during quarter q. Finally, π are the set of airline-route fixed-effects that control for any time-invariant airline and route-specific characteristics that affect price dispersion.

In contrast to equation (2), $Holiday$ and $Weekend$ are not included because the DB1B does not include information on the exact purchase and departure dates for each ticket. For this same reason, we also are not able to include $CovidOutbreakBook$ to indicate whether the ticket was purchased during the pre-pandemic or pandemic periods. However, $2020Q3$ should capture this effect. Since the fourth quarter of 2019 serves as the comparison group, the sign of the coefficient on $2020Q3$ indicates whether price dispersion increased or decreased relative to the level of price dispersion observed prior to the pandemic (i.e., during $2019Q4$).

The results of estimating equation (3) with airline-route fixed effects are provided in Table 3. Consistent with Table 2, the positive and statistically significant coefficient on $2020Q3$ across all specifications confirms that price dispersion increased during the pandemic. Furthermore, the positive and statistically significant coefficients on $CovidOriginQuarter$ and $CovidDestQuarter$ indicate that an increase in new COVID-19 cases at the origin or destination are also associated with higher levels of price dispersion. Finally, the negative sign on $Flights$ is consistent with our previous results while $Carriers$ is positive but statistically insignificant.

Table 3: Price dispersion results with DB1B fares

	(1)	(2)	(3)
Dependent variable:	$\text{Gini}^{\text{lodd}}$	$\text{Gini}^{\text{lodd}}$	$\text{Gini}^{\text{lodd}}$
Estimator:	FE-OLS	FE-OLS	FE-2SLS
$2020Q3$	0.128***	0.105***	0.101***
	(0.002)	(0.004)	(0.007)
CovidOriginQuarter		0.005***	0.005***
		(0.001)	(0.001)
CovidDestQuarter		0.006***	0.005***
		(0.001)	(0.001)
Carriers			0.082
			(0.053)
Flights			-0.015**
			(0.006)
R^2	0.119	0.121	0.114
Observations	93,756	93,756	62,554
Kleibergen-Paap rk LM statistic			23.092***

Notes: Summary statistics are provided in Appendix Table A1. All specifications include airline-route fixed-effects. Constant is included but not reported. *Carriers* and *Flights* in column (3) are treated as endogenous variables and instrumented for using past-year values of *Carriers* and *Flights* in addition to the interaction between the average daily jet fuel price in each quarter and route distance. The null hypothesis of the Kleibergen-Paap rk LM statistic is that the equation is underidentified. First-stage estimates are reported in Appendix Table A3. Standard errors are clustered by route. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

6 Conclusion

In this article, we documented how the economic slowdown caused by the COVID-19 pandemic affected intertemporal price dispersion in the U.S. airline industry. Exploiting a unique panel of over 43 million fares collected before and during the pandemic, we find that airlines discounted ticket prices by an average of 57% in the months after COVID-19 was declared a national emergency. The rate of intertemporal price increases also declined, particularly in the last week to departure. We also find that an increase in new COVID-19 cases at the destination decreases fares while an increase in new cases at the origin has no statistically measurable effects.

Although previous research suggests that airline price dispersion is pro-cyclical, we find that price dispersion actually *increased* during the COVID-19 recession. Consistent with our intertemporal pricing results, we find that an increase in new COVID-19 cases at the destination increases price dispersion while an increase in new cases at the origin has no statistically measurable effects. Even though our findings differ from Cornia et al. (2012), the economic slowdown caused by COVID-19 has been unique in the aspect that adverse supply and demand shocks have permeated across many industries. Consequently, it is not surprising that previous patterns may not extend to the COVID-19 recession.

The analysis presented in this article offer some interesting avenues for future research. Since COVID-19 has likely had differential impacts across industries, it would be interesting to determine if similar price dispersion impacts have also occurred in other oligopolistic industries such as the automobile, gasoline, grocery, hotel, or shipping industries. Future work could also extend the present analysis to airline markets in other countries or regions. Since the diffusion of COVID-19 and the arrival of new variants has been heterogeneous across regions, it would be interesting to see if similar intertemporal pricing patterns are observed in the African, Australian, Asian, European, or South American airline markets.

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Appendix A: Supplementary Tables

Table A1: Descriptive Statistics

Intertemporal pricing regressions: equation (1)

Variable	Mean	Std. dev.	Min	Max	Obs.
Fare	167.17	132.63	11.00	6,155	43,160,581
DaysToDeparture 1-2	0.03	0.17	0.00	1.00	43,160,581
DaysToDeparture 3-6	0.06	0.24	0.00	1.00	43,160,581
DaysToDeparture 7-13	0.11	0.31	0.00	1.00	43,160,581
DaysToDeparture 14-20	0.11	0.31	0.00	1.00	43,160,581
DaysToDeparture 21-60	0.69	0.46	0.00	1.00	43,160,581
CovidOutbreak	0.35	0.48	0.00	1.00	43,160,581
CovidOrigin (in 1,000s)	0.66	1.69	0.00	11.93	43,160,581
CovidDest (in 1,000s)	0.75	1.93	0.00	11.93	43,160,581

Price dispersion regressions: equation (2)

Variable	Mean	Std. dev.	Min	Max	Obs.
$\text{Gini}^{\text{lodd}}$	-1.98	0.97	-10.43	1.27	937,636
Carriers	2.78	1.61	0.00	8.00	937,636
Flights	15.40	10.84	0.00	50.00	937,636
Holiday	0.03	0.17	0.00	1.00	937,636
Weekend	0.27	0.44	0.00	1.00	937,636
CovidOutbreakBook	0.44	0.47	0.00	1.00	937,636
CovidOriginBook (in 1,000s)	0.84	1.74	0.00	11.38	937,636
CovidDestBook (in 1,000s)	0.96	1.98	0.00	11.62	937,636
Instruments					
Past-year carriers	2.70	1.57	0.00	7.00	937,636
Past-year flights	15.45	11.40	0.00	57.00	937,636
Fuel price	1.27	0.48	0.41	1.98	937,636
Fuel price × Distance (in 100s of miles)	16.69	11.78	0.96	53.54	937,636

Price dispersion regressions with DB1B fares: equation (3)

Variable	Mean	Std. dev.	Min	Max	Obs.
$\text{Gini}^{\text{lodd}}$	-1.16	0.31	-3.63	4.02	93,756
2020Q3	0.37	0.48	0.00	1.00	93,756
CovidOriginQuarter (in 1,000s)	0.85	1.81	0.00	6.40	93,756
CovidDestQuarter (in 1,000s)	0.85	1.81	0.00	6.40	93,756
Carriers	0.47	0.85	0.00	7.00	93,756
Flights	1.21	2.88	0.00	41.00	93,756
Instruments					
Past-year carriers	0.50	0.90	0.00	6.00	93,756
Past-year flights	1.46	3.48	0.00	49.00	93,756
Fuel price × Distance (in 100s of miles)	19.92	13.65	0.45	153.09	93,756

Table A2: First-stage estimates for Table 2

Dependent variable	(1) *Carriers*	(2) *Carriers*	(3) *Flights*	(4) *Flights*
Past-year Carriers	0.312***	0.312***	-0.323***	-0.327***
	(0.042)	(0.043)	(0.099)	(0.099)
Past-year Flights	0.003**	0.003**	0.506***	0.507***
	(0.001)	(0.001)	(0.028)	(0.028)
Jet Fuel Price	-0.076***	-0.073***	-0.959***	-0.888***
	(0.022)	(0.022)	(0.155)	(0.166)
Jet Fuel Price × Distance	0.002	0.002	0.035***	0.035***
	(0.001)	(0.001)	(0.010)	(0.011)
Holiday	-0.016**	-0.016**	-1.293***	-1.294***
	(0.007)	(0.007)	(0.128)	(0.128)
Weekend	0.008	0.008	-0.739***	-0.738***
	(0.006)	(0.006)	(0.096)	(0.096)
CovidOutbreakBook		0.012		0.337***
		(0.020)		(0.128)
CovidOriginBook		-0.009		-0.103**
		(0.009)		(0.041)
CovidDestBook		-0.000		-0.045
		(0.008)		(0.031)
R^2	0.072	0.072	0.379	0.380
Observations	936,241	936,241	936,241	936,241

Notes: All specifications include flight-number fixed effects that control for any flight-invariant characteristics that do not differ across departure dates (e.g., distance, operating carrier, and time-of-departure). Constant and month-of-departure dummies are included but not reported. Standard errors are clustered by route. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table A3: First-stage estimates for Table 3

	(1)	(2)
Dependent variable	*Carriers*	*Flights*
Past-year carriers	0.197***	0.280
	(0.043)	(0.199)
Past-year flights	-0.033**	-0.411***
	(0.015)	(0.133)
Fuel price × Distance	0.001	-0.059***
	(0.001)	(0.004)
2020Q3	-0.050***	-1.051***
	(0.010)	(0.057)
CovidOriginQuarter	-0.008***	-0.053***
	(0.002)	(0.009)
CovidDestQuarter	-0.007***	-0.052***
	(0.002)	(0.009)
R^2	0.077	0.174
Observations	62,554	62,554

Notes: All specifications include airline-route fixed effects. Constant is included but not reported. Standard errors are clustered by route. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.