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 U.S. domestic airline market. Applying fixed effect techniques to a unique panel of 43 million fares collected before and after the outbreak of the pandemic, we find that airlines discounted fares by an average of 57% in the first five months of the pandemic, and that prices intertemporally increased at a lower rate, particularly in the last week to departure. As a consequence, flight-level price dispersion decreased. These findings are consistent with the theoretical predictions arising from models of stochastic peak-load pricing (i.e., the drastic decline in the demand for business travel during the pandemic decreases the shadow cost of capacity, resulting in lower fares and lower increases in fares) and intertemporal price discrimination (i.e., the decline in the share of business travel resulted in airlines adjusting their intertemporal pricing strategy by decreasing the rate at which fares increased for late-booking passengers).

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 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 previous recessions were not caused by a pandemic, 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

[1] Other studies that examine airline price dispersion include Aryal et al. (2023); Borenstein and Rose (1994); Kim et al. (2021); Gaggero and Piga (2011); Gerardi and Shapiro (2009); Hayes and Ross (1998); Mantin and Koo (2009); Orlov (2011); Sengupta and Wiggins (2014).

the airline industry. As governments imposed travel restrictions to 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 9/11 terrorist attack, 2003 SARS outbreak, 2008 financial crisis, or the 2009 swine flu pandemic).

Another unique aspect of the COVID-19 recession relative to previous recessions are the unprecedented airline responses. In addition to adjusting capacity and flight schedules, most U.S. airlines waived cancellation and change fees during the pandemic. Since these ticket restrictions are an important element of product differentiation, the COVID-19 pandemic provides an interesting setting to explore how price dispersion changes when a key element of product differentiation is suddenly eliminated.

Nonetheless, changes in the mix of traveling passengers and the severe decline in air travel demand during the COVID-19 pandemic allow us to test the theoretical predictions arising from models of intertemporal price discrimination and stochastic peak-load pricing (Borenstein and Rose, 1994; Cornia et al., 2012).

Intertemporal price discrimination refers to the practice of charging different prices during the booking period, and in particular, higher prices to inelastic late-booking passengers (typically business travelers). As a result of the drastic decline in the demand for business travel, the mix of traveling passengers during the pandemic was more homogeneous and comprised of a larger proportion of leisure travelers.[2] Given the reduction in the share of business travel, the rate of intertemporal price increases in the last few weeks to departure is expected to be lower during the pandemic, resulting in a decrease in price dispersion.

This theoretical prediction also arises in models of stochastic peak-load pricing. In these models, the optimal peak-load price reflects marginal operating costs plus a charge based on the probability that demand will exceed capacity at the time the ticket is sold and the

[2]U.S. companies' travel budgets declined by 90% or more in 2020. See https://time.com/6108331/business-travel-decline-covid-19/ and https://www2.deloitte.com/us/en/insights/focus/transportation/future-of-business-travel-post-covid.html.

expected shadow cost of capacity if demands ends up exceeding capacity (Borenstein and Rose, 1994; Crew and Kleindorfer, 1986). Given that business travel demand drastically declined during the pandemic, demand was unlikely to exceed capacity during the late part of the booking period, implying that the shadow cost of capacity fell. These lower shadow costs are expected to translate to lower fares, lower increases in fares, and thus, lower price dispersion.

To determine how COVID-19 affects both price levels and intertemporal price dispersion, we exploit a unique panel of over 43 million fares. 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.[3] 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 four main findings. Foremost, as COVID-19 spread across the country, airlines responded by discounting fares by an average of 57%.[4] 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 decreased during the pandemic. As we previously discussed, these findings are consistent with the theoretical predictions arising from models of intertemporal price discrimination (i.e., the decline in the share of business travel resulted in airlines adjusting

[3]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.

[4]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`.

their intertemporal pricing strategy by decreasing the rate at which fares increased for late-booking passengers) and stochastic peak-load pricing (i.e., the sharp decline in travel demand during the pandemic decreased the shadow cost of capacity, resulting in lower fares and lower increases in fares).

Although we find that pandemic fare decreases are driven primarily by the diffusion of COVID-19, there is slightly more emphasis on the spread at the destination relative to the origin. We believe these findings are sensible from the passenger perspective. In particular, since shutdowns and other pandemic restrictions are highly correlated with the local number of COVID-19 cases, travelers leaving home (i.e., the origin market) will only care about restrictions that are in effect at the destination because restrictions at the origin likely do not affect the utility of their trip. For example, most leisure travelers do not want to travel to markets where restaurants, bars, museums, and other attractions are closed due to local pandemic restrictions. Similarly, most business travelers do not want to travel to markets where in-person meetings are not possible due to regional office closures. As a result, 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 likelihood of new pandemic restrictions being introduced at the destination increases.

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. Section 6 presents robustness checks. Finally, Section 7 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

Our fare and itinerary data are obtained from a major OTA.[5] 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.

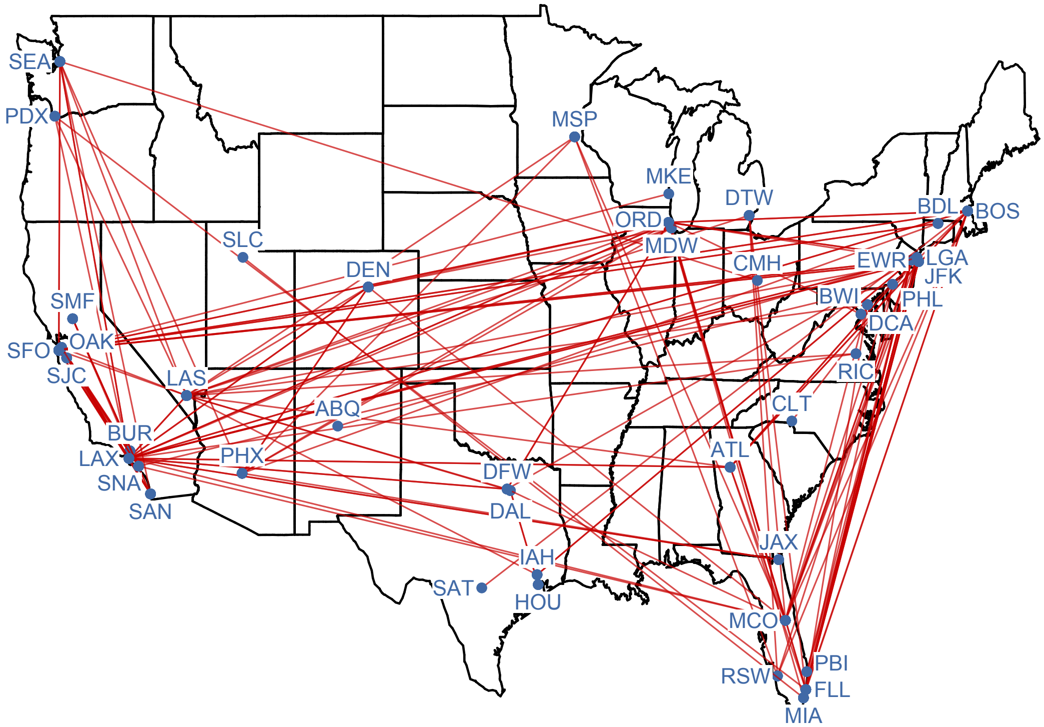
To construct our analysis sample, data were collected for flights departing between October 1st, 2019 and August 31st, 2020. Daily economy-class fare quotes were collected for one-way travel between each of the directional airport-pairs in Figure 1.[7] For each route,

[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 (2023), 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 Alderighi et al. (2022), 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 duration. For example, fares for two-day trips are likely different from seven or ten-day trips. Moreover, due to our focus on economy-class tickets, we do not study product differentiation across

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



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.[8]

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

fare classes (e.g., business or first-class tickets).

[8]Previous studies that examine airline price dispersion in the U.S. market typically rely on the U.S. Department of Transportation's Airline Origin and Destination Survey (DB1B). For example, see Borenstein and Rose (1994), Gerardi and Shapiro (2009), and Cornia et al. (2012). 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.

(Allegiant, Frontier, JetBlue, Spirit, and Sun Country).[9]

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.[10] 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 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.[11] Furthermore, since jet fuel prices affect the marginal cost of serving a given route, we also collect daily jet fuel prices from the U.S. Energy Information Administration to construct additional instruments.[12]

[9] 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 market structure variable (e.g., the Herfindahl-Hirschman Index).

[10] 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.

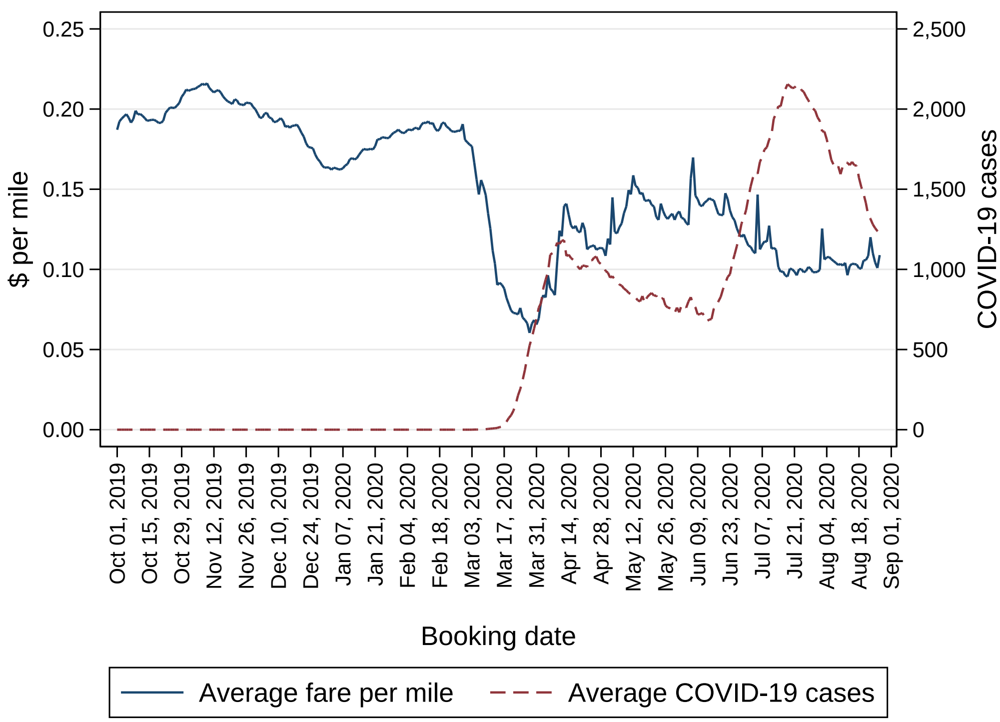
[11] See `https://transtats.bts.gov/Fields.asp?gnoyr_VQ=FGK`.

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

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* 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.[13]

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



To relate the pricing decision of airlines to the diffusion of the COVID-19 pandemic, we

[13]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 26th, 2020. For example, booking dates in August 2020 include flights that depart in August, September, and October 2020.

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.[14] 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 (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.

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,

[14] 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 3: Average nonstop fare per mile by days to departure and month of departure

(a) Full-service carriers

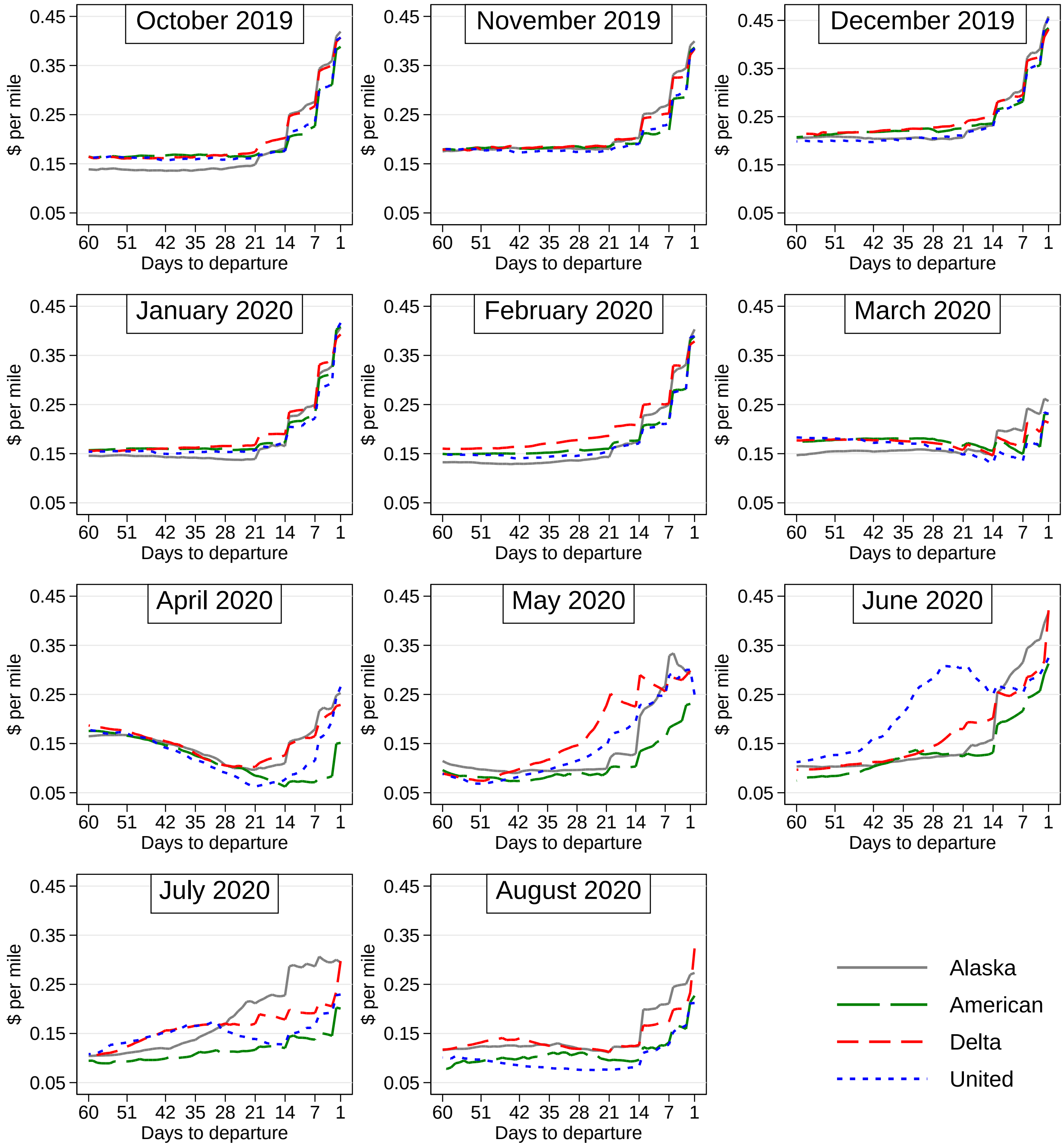
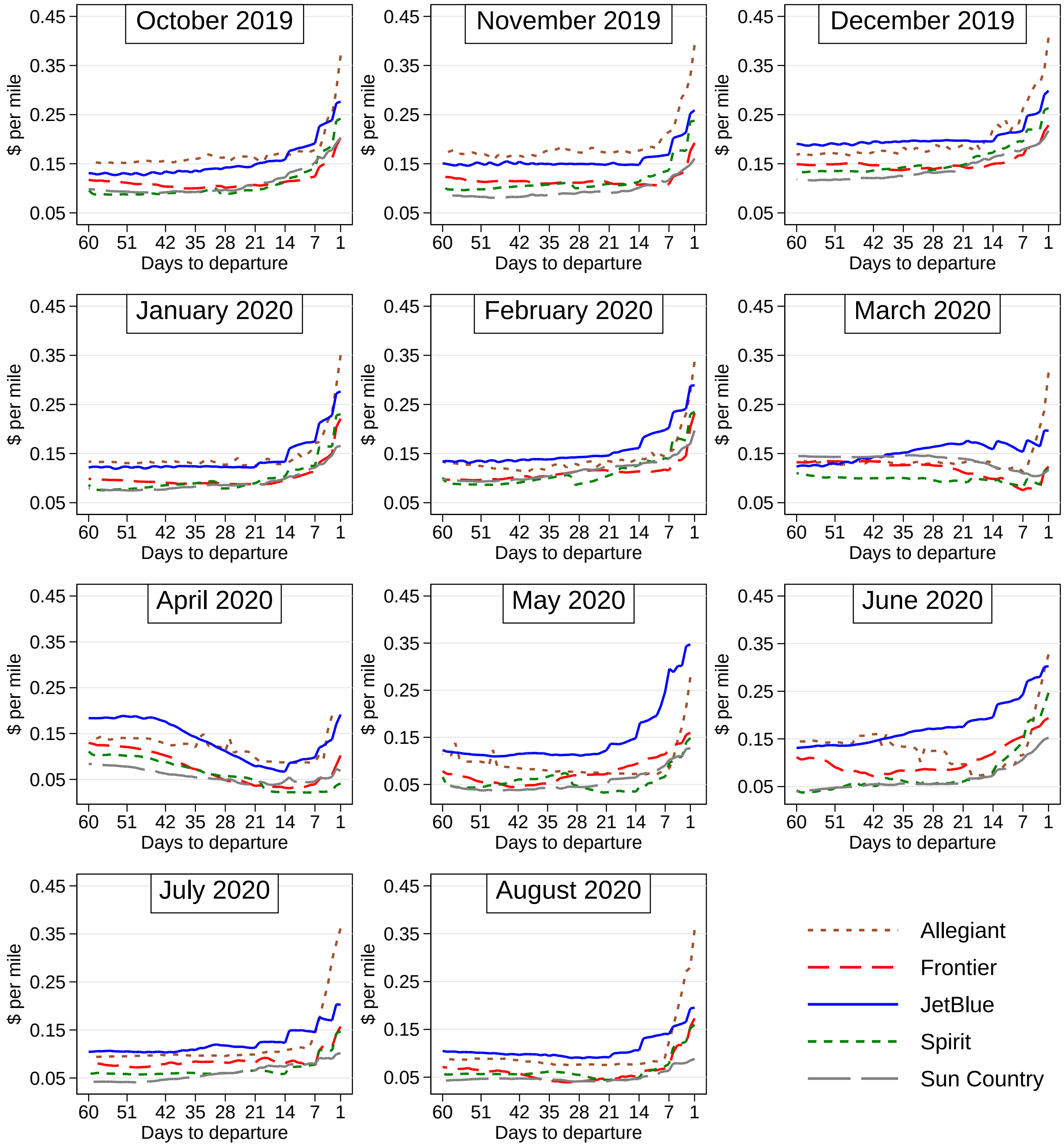


Figure 3: Average nonstop fare per mile by days to departure and month of departure (cont.)

(b) Low-cost carriers



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 departure observed in March were likely due to the pandemic, we cannot definitively state that these changes were solely due to COVID-19.[15]

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.[16] 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, average fares do not monotonically increase as the departure date approaches. Moreover, the pricing curves for each of the FSCs do not overlap in the same manner as the pre-pandemic diagrams (e.g., compare the July 2020 diagram with the October 2019 diagram in Panel A of Figure 3). For instance, the irregular pricing curves for United and Alaska in July 2020 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 revenue 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

[15]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.

[16]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.

drop in demand induced by the diffusion of COVID-19.[17]

A similar argument generally applies to LCCs. However, it is worth noting that JetBlue, one of the major LCCs in the U.S., displays a different pricing pattern than Allegiant, a minor LCC. In particular, JetBlue gradually increases fares at three weeks, two weeks, and one week prior to departure, whereas Allegiant fares stay relatively stable until seven days prior to departure when fares begin to substantially increase. This finding may be suggestive of leader-follower behavior amongst LCCs (Bergantino et al., 2018; Kim et al., 2021).

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, average fares remain lower than those observed during the pre-pandemic period for both FSCs and LCCs.

[17]For example, at the Airline Group of the International Federation of Operations Research (AGIFORS) conference, Richard Cleaz-Savoyen, the Managing Director of Revenue Optimization at Air Canada, stated that: "all of our forecasting techniques developed over the years became incorrect and at the beginning of the pandemic, revenue management became manual and very much micromanaged on a day-by-day basis" (Garrow and Lurkin, 2020). His view was shared by other airline representatives at the conference. For instance, Sander Stomph, the Vice President at KLM Royal Dutch Airlines, mentioned that KLM's machine learning algorithms were not forecasting well because the historical data they were trained on were from a very different era, and therefore no longer valid (Garrow and Lurkin, 2020).

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),

$$
\begin{aligned}
\log(Price_{rafdb}) \;=\; & \sum_{i=1}^{4}\delta_i \cdot DaysToDeparture_{ib} + \gamma \cdot CovidOutbreak_b + \\
& + \sum_{i=1}^{4}\gamma_i \cdot CovidOutbreak_b \times DaysToDeparture_{ib} + \\
& + \alpha \cdot CovidOrigin_{rdb} + \beta \cdot CovidDest_{rdb} + \\
& + \pi \cdot CovidOutbreak \times LCC + \rho_{rafd} + \varepsilon_{rafdb} \qquad (1)
\end{aligned}
$$

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.[18] 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 affect fares.[19] Note that this fixed effects approach does not control for variables that

[18] 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.

[19] 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 at-

are time-varying during the booking period (e.g., available capacity). For example, low fares may result from a low volume of tickets sold during the booking period.

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 7-day moving average of new positive COVID-19 cases (in thousands) in the state of the origin airport. Similarly, $CovidDest$ is the 7-day moving average of new positive COVID-19 cases (in thousands) 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 variable $CovidOutbreak \times LCC$ interacts $CovidOutbreak$ with a low-cost carrier indicator to test whether the impact of the pandemic on fares differs by carrier type.

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.

tributable 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.

Finally, ε is the error term. We estimate the fixed effects model described by equation (1) using ordinary least squares (OLS) with standard errors 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.[20] 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).[21]

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 Adjusted 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

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

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

Table 1: Intertemporal pricing results

Dependent variable:	(1) ln(Price)	(2) ln(Price)	(3) ln(Price)	(4) ln(Price)	(5) ln(Price)
DaysToDeparture 1-2	0.679***	0.756***	0.806***	0.806***	0.806***
	(0.019)	(0.019)	(0.023)	(0.023)	(0.023)
DaysToDeparture 3-6	0.444***	0.517***	0.543***	0.543***	0.543***
	(0.024)	(0.022)	(0.027)	(0.027)	(0.027)
DaysToDeparture 7-13	0.216***	0.275***	0.274***	0.274***	0.274***
	(0.020)	(0.018)	(0.020)	(0.020)	(0.020)
DaysToDeparture 14-20	0.021***	0.067***	0.073***	0.073***	0.073***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
CovidOutbreak		-0.835***	-0.814***	-0.814***	-0.755***
		(0.029)	(0.031)	(0.031)	(0.032)
CovidOutbreak × DaysToDeparture 1-2			-0.156***	-0.137***	-0.136***
			(0.021)	(0.022)	(0.022)
CovidOutbreak × DaysToDeparture 3-6			-0.086***	-0.069***	-0.068***
			(0.024)	(0.024)	(0.024)
CovidOutbreak × DaysToDeparture 7-13			-0.007	0.008	0.009
			(0.016)	(0.015)	(0.015)
CovidOutbreak × DaysToDeparture 14-20			-0.025***	-0.013*	-0.013*
			(0.008)	(0.008)	(0.008)
CovidOrigin				-0.002	-0.002
				(0.005)	(0.006)
CovidDest				-0.019***	-0.019***
				(0.004)	(0.004)
CovidOutbreak × LCC					-0.284***
					(0.049)
Adjusted R^2	0.171	0.300	0.302	0.303	0.306
Observations	43,160,581	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 (e^{β}-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.

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 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 Panel B of Figure 3, 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 Panel A of Figure 3 for full-service carriers during the pandemic months (e.g., Alaska in May-August 2020 or American and Delta in June 2020).

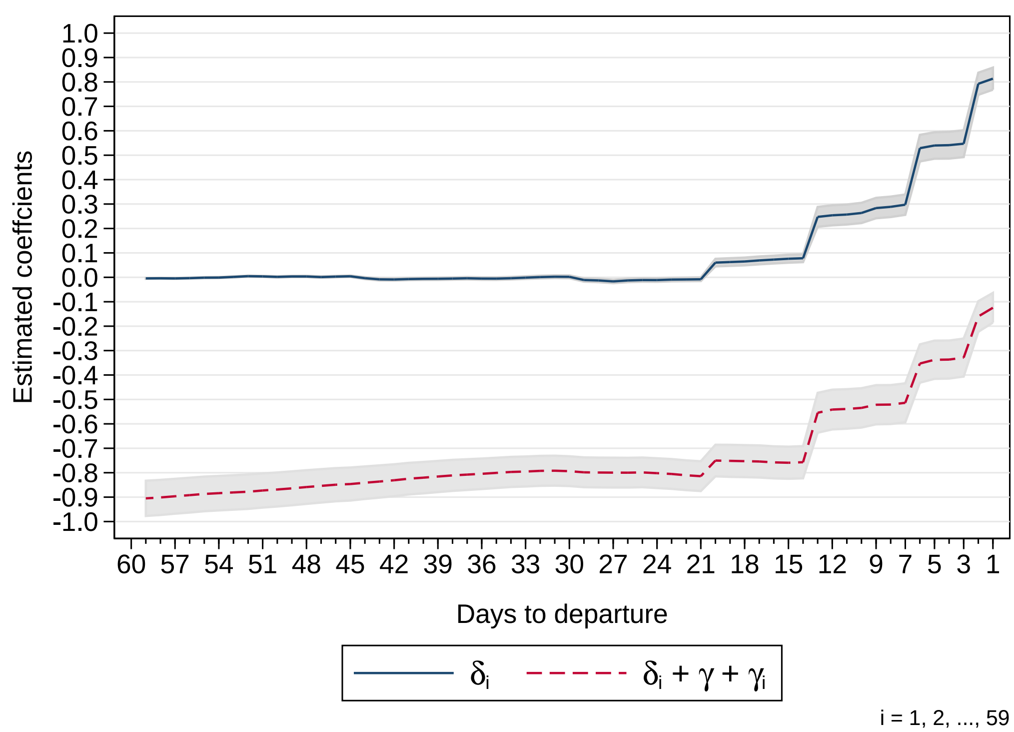
To examine how heterogeneity in the diffusion of COVID-19 affects fares, column 4 adds the 7-day moving average number of new positive COVID-19 cases in the origin ($CovidOrigin$) and destination ($CovidDest$) states to the specification presented in column 3. The coefficients on $CovidOrigin$ and $CovidDest$ 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 finding is sensible. In particular, the origin typically represents the home market of the passenger. Considering that shutdowns and other pandemic restrictions are highly correlated with the local number of COVID-19 cases, passengers leaving home will only care about restrictions that are in effect at the destination because restrictions at the origin likely do not affect the utility of their trip. For example, most leisure travelers do not want to travel to markets where restaurants, bars, museums, amusement parks, and other attractions are closed due to pandemic restrictions. Similarly, most business travelers do not want to travel to markets where in-person meetings are not possible due to local office closures. Accordingly, 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 likelihood of new pandemic restrictions being introduced at the destination increases. 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.

To investigate whether pandemic pricing differed between FSCs and LCCs, column 5 adds the interaction between $CovidOutbreak$ and a LCC indicator. The negative and statistically significant coefficient on $CovidOutbreak \times LCC$ indicates that LCC fares were on average 24.7% lower than FSC fares during the pandemic months of our sample. Relative to the pre-pandemic period, FSC fares were 53% lower and LCC fares 64.6% lower.

To further examine intertemporal pricing, we perform a sensitivity check on our days to departure groupings (which in equation (1) are grouped into five mutually exclusive intervals) by replacing the four days to departure variables with daily dummies (i.e., an indicator for each day to departure). We then re-estimate equation (1). In lieu of presenting a lengthy table with coefficient estimates for each of the 59 days to departure dummies and corresponding interactions with $CovidOutbreak$, results from this sensitivity are presented graphically in Figure 4.

Figure 4: Estimated coefficients on the daily DaysToDeparture dummies with 95% confidence interval during the pre-pandemic and pandemic periods



The solid blue line in Figure 4 plots the estimated coefficients on the 59 days to departure dummies (i.e., intertermporal pricing during the pre-pandemic months) while the dashed red line plots the linear combination of the *DaysToDeparture* dummies and *CovidOutbreak* variables (i.e., intertemporal pricing during the pandemic months of our sample). The shaded gray area encompassing the solid blue and dashed red lines represents the 95% confidence interval. Consistent with the descriptive analysis presented in Section 3, the dashed red line in Figure 4 demonstrates that both fares and the rate of intertemporal price increases are lower during the pandemic months of our sample (especially in the last week to departure).[22] Relative to the solid blue line (pre-pandemic period), the height of the price jumps from seven to six and three to two days before departure are smaller in the dashed red line (pandemic period). Stated differently, the absolute variation on the Y-axis when moving from 7 to 1 day prior to departure is approximately 0.5 for the solid blue line (moving from 0.3 to 0.8) and less than 0.4 for the dashed red line (moving from -0.5 to -0.1).

Finally, note that four well-defined fare hikes are observed from twenty-one to twenty, fourteen to thirteen, seven to six, and three to two days prior to departure in Figure 4. These fare hikes are consistent with those reported in our descriptive analysis (see Figure 3) and support our initial grouping of days to departure categories into the set of five mutually exclusive intervals used in our baseline specification of equation (1).

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

[22]Coefficients on the non-interacted Covid variables in this sensitivity are qualitatively similar to the coefficients reported in Table 1. For example, the coefficient on *CovidOutbreak* is -0.903 and statistically significant at the 1% level. Similarly, the coefficient on *CovidOrigin* is small in magnitude (-0.006) and statistically insignificant whereas the coefficient on *CovidDest* is -0.022 and statistically significant at the 1% level.

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 changed 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.

As discussed in Section 1, the expected impact of the COVID-19 pandemic on price dispersion is negative. In models of stochastic peak-load pricing, the drastic decline in business travel demand during the pandemic should decrease the shadow cost of capacity, resulting in lower fares and lower increases in fares. Similarly, in models of intertemporal price discrimination, the decline in the share of business travel during the pandemic should result in airlines adjusting their intertemporal pricing strategy by decreasing the rate at which fares increase in the last few weeks to departure, leading to lower price dispersion.

5.1 Econometric Model of Price Dispersion

Our model of price dispersion is summarized by the following equation,

$$\begin{aligned} PriceDisp_{rafd} \;=\;& \phi \cdot MktShr_{rad} + \theta \cdot HHI_{rd} + \sigma \cdot Holiday_d + \delta \cdot Weekend_d + \\ & + \gamma_1 \cdot \mathbb{1}_1(\textit{Dep. March13-May12})_d + \gamma_2 \cdot \mathbb{1}_2(\textit{Dep. after May12})_d + \\ & + \alpha \cdot CovidOriginBook_{rd} + \beta \cdot CovidDestBook_{rd} + \lambda_{raf} + \nu_{rafd} \quad (2) \end{aligned}$$

where the dependent variable $PriceDisp$ stands for price dispersion, which we measure using several different metrics (Cui et al., 2019). First, consistent with many previous studies of the airline industry, we measure price dispersion using the Gini coefficient of inequality (Borenstein and Rose, 1994; Gaggero and Piga, 2011; Gerardi and Shapiro, 2009; Kim et al., 2021). Specifically, we use the Gini log-odds ratio, $ln[Gini/(1-Gini)]$, which is employed to unbound the inequality index.[23] We adopt different nuances of this inequality index: the Gini coefficient computed using all fares collected during the sixty-day booking period of each flight f, $Gini^{lodd}$, and then the same coefficient using only fares collected in the last 30 or the last 20 days before departure ($Gini30^{lodd}$ and $Gini20^{lodd}$, respectively).[24] Other measures of price dispersion employed as the dependent variable in equation (2) are the natural logarithm of the flight-level coefficient of variation (CV)[25] and the natural logarithm of the flight-level price range (i.e., $P_{\max} - P_{\min}$ measures the difference between the maximum and minimum fare of the price distribution).[26]

Similar to equation (1), r refers to the route, a the airline, and f the flight; the combination

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

[24] Since Figures 3 and 4 demonstrate that fare changes are limited between 21 and 60 days before departure, $Gini30^{lodd}$ and $Gini20^{lodd}$ examine whether price dispersion estimates are affected by the duration of the booking period used to compute the Gini coefficient.

[25] The flight-level coefficient of variation is the ratio of the standard deviation of the price distribution to the mean of the price distribution.

[26] Because several flights were canceled during the pandemic, the average number of fare observations for each flight f is 42. We restrict the calculation of each price dispersion metric to f's with more than 10 observations, since this threshold reduces potential small sample bias (Deltas, 2003).

raf identifies the individual component of the panel. The time dimension of the panel is now d, the date-of-departure for flight f. Consistent with the price dispersion specification in Gaggero and Piga (2011), we refer to λ as the set of flight-code fixed effects. Since an observation in this analysis is the price dispersion of an individual flight, these flight-code fixed effects control for any flight-code-invariant characteristics that do not differ across departure dates (e.g., route, operating carrier, and time-of-departure).[27] 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 the level of competition has on price dispersion, we include the airline's market share on the route ($MktShr$) and the route's Herfindahl-Hirschman Index (HHI). These two regressors are computed using the daily number of nonstop flights on the route to better capture the competition that each airline faces on the route on a given day (Bergantino and Capozza, 2015b).

Due to the possible simultaneity of price and quantity, $MktShr$ and HHI are treated as endogenous variables and equation (1) is estimated using two-stage least squares (2SLS). We correct for this potential endogeneity using four instruments: (i) the airline's market share on the route on the same corresponding day during the previous year,[28] (ii) the Herfindahl-Hirschman Index of the route on the same corresponding day during the previous year,

[27]Given the daily time dimension of our panel, the fixed effects in equation (2) are different than those used in previous studies that rely on quarterly data (e.g., Gerardi and Shapiro, 2009; Cornia et al., 2012; Kim et al., 2021). Instead of employing separate carrier-route and quarter fixed effects (e.g., Gerardi and Shapiro, 2009; Cornia et al., 2012), we employ flight-code fixed effects to allow for the possibility that price dispersion for an airline's flights on the same route differ across flight codes (e.g., time-of-day). For example, due to factors that we do not observe, the 7:05am Delta flight from Atlanta to Boston (flight code DL 327) may display a different price dispersion pattern over time than the 5:00pm Delta flight from Atlanta to Boston (flight code DL 360).

[28]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 airline's market share on a given route on Tuesday October 1st, 2019 is paired with the airline's market share on same route on Tuesday October 2nd, 2018.

(iii) the daily jet fuel price,[29] 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.[30] 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.[31] We expect lower fare dispersion on holidays due to systematic peak-load pricing (Gaggero and Piga, 2011). $Weekend$ is an indicator equal to one if flight f departs on a Saturday or Sunday. We expect lower fare dispersion on weekends due to a more homogeneous mix of passengers (i.e., business travelers typically do not fly on weekends).

The variables of interest in equation (2) are those that capture the effect of the pandemic on price dispersion: $\mathbb{1}_1$*(Dep. Mar13-May12)*, $\mathbb{1}_2$*(Dep. after May12)*, $CovidOriginBook$, and $CovidDestBook$. The first two regressors are indicators that specify the departure date of the flight: $\mathbb{1}_1$*(Dep. Mar13-May12)* equals one if the flight departs between March 13th, 2020 and May 12th, 2020 while $\mathbb{1}_2$*(Dep. after May12)* equals one for flights departing after May 12th, 2020. Because our fare collection begins sixty days prior to departure, the set of fares used to calculate price dispersion for flights indexed by $\mathbb{1}_1$*(Dep. Mar13-May12)* are collected in both the pre-pandemic and pandemic periods, whereas the set of fares used to calculate price dispersion for flights indexed by $\mathbb{1}_2$*(Dep. after May12)* are collected entirely during the pandemic. Flights departing prior to the pandemic's outbreak in the U.S. comprise the omitted category in the regression (i.e., flights departing before March 13th, 2020).

[29]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 price quote.

[30]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).

[31]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.

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-code fixed effects and 2SLS are provided in Table 2. The first three columns present results for three different nuances of the Gini coefficient, the fourth column presents results when the natural logarithm of the coefficient of variation is the dependent variable, and the fifth column presents results when the natural logarithm of the price range is the dependent variable. Column (1) represents our preferred specification since it is the closest to those adopted in Gerardi and Shapiro (2009) and Gaggero and Piga (2011).

The positive and statistically significant coefficient on $MktShr$ suggests that an increase in an airline's market share on a route enables the airline to better intertemporally price discriminate, which ultimately results in a higher level of price dispersion (Gaggero and Piga, 2011). HHI is also positive and statistically significant at conventional levels, indicating that a decrease in competition increases price dispersion. This finding is consistent with the results in Gerardi and Shapiro (2009) who find 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).

The negative and statistically significant coefficient on $Holiday$ is consistent with the results in Gaggero and Piga (2011), who find lower levels of price dispersion for flights departing during holiday periods. Due to systematic peak-load pricing, fares are higher and

Table 2: Price dispersion results

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	$Gini^{lodd}$	$Gini30^{lodd}$	$Gini20^{lodd}$	ln(CV)	$\ln(P_{max} - P_{min})$
Estimator:	FE-2SLS	FE-2SLS	FE-2SLS	FE-2SLS	FE-2SLS
MktShare	1.097***	0.415*	0.758*	0.810***	-0.979***
	(0.216)	(0.225)	(0.415)	(0.180)	(0.225)
HHI	0.541***	0.159	2.660***	0.414***	-2.172***
	(0.186)	(0.300)	(0.656)	(0.153)	(0.218)
Holiday	-0.045***	-0.152***	-0.154***	-0.075***	0.048***
	(0.013)	(0.017)	(0.024)	(0.012)	(0.016)
Weekend	-0.022***	-0.078***	-0.075***	-0.035***	0.062***
	(0.005)	(0.008)	(0.011)	(0.005)	(0.011)
$\mathbb{1}_1$(Dep. Mar13-May12)	-0.088**	-0.027	-0.207***	-0.177***	-0.225***
	(0.041)	(0.049)	(0.056)	(0.036)	(0.034)
$\mathbb{1}_2$(Dep. after May12)	-0.359***	-0.138***	-0.336***	-0.388***	-0.628***
	(0.050)	(0.053)	(0.058)	(0.042)	(0.047)
CovidOriginBook	-0.005	0.005	0.009	-0.001	-0.010
	(0.016)	(0.013)	(0.023)	(0.013)	(0.015)
CovidDestBook	0.026**	-0.006	0.001	0.025**	0.019
	(0.011)	(0.011)	(0.018)	(0.010)	(0.015)
R^2	0.055	0.010	0.010	0.045	0.131
Observations	787,994	569,272	499,726	787,994	787,994
K-P LM statistic	55.929***	48.141***	39.119***	55.929***	55.929***
K-P Wald F statistic	30.607***	21.479***	14.957**	30.607***	30.607***

Notes: Summary statistics are provided in Appendix Table A1. All specifications include flight-code fixed effects that control for any flight-code-invariant characteristics that do not differ across departure dates (e.g., route, operating carrier, and time-of-departure). Constant is included but not reported. Standard errors are clustered at the route-level. $MktShr$ and HHI are treated as endogenous variables and instrumented for using past-year values of $MktShr$ and HHI 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.

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).

The second part of Table 2 is new to the price dispersion literature and presents the impact of COVID-19 on price dispersion. The negative and statistically significant coefficients on $\mathbb{1}_1$*(Dep. Mar13-May12)* and $\mathbb{1}_2$*(Dep. after May12)* indicate that fares collected during the pandemic exhibit *less* price dispersion than similar fares collected prior to the pandemic. It is worth noting that, in all Table 2 specifications, the absolute value of the coefficient on $\mathbb{1}_2$*(Dep. after May12)* is larger than the absolute value of the coefficient on $\mathbb{1}_1$*(Dep. Mar13-May12)*. This result is sensible since it indicates that lower levels of price dispersion are observed when *all* fares, rather than *some* fares, are collected during the pandemic.

The finding that flights during the pandemic exhibit lower price dispersion is consistent with our analysis of intertemporal pricing (e.g., see Figure 3, Figure 4, and Table 1) that documented a lower rate of fare hikes in the last week to departure, suggesting that price dispersion decreased during the pandemic. This result is likely reflective of a more homogeneous passenger mix, with a lower proportion of business travelers flying during the pandemic. A similar conclusion is reached by Morlotti and Redondi (2023) with European data. Alternatively, this finding is also consistent with the theoretical prediction arising from stochastic peak-load pricing models. Due to the drastic decline in business travel demand, the shadow cost of capacity fell during the pandemic, resulting in lower fares, lower increases in fares, and thus, lower price dispersion.

The evidence on $CovidOriginBook$ and $CovidDestBook$ is mixed, with the coefficients on these variables often statistically insignificant. Since $CovidOriginBook$ and $CovidDestBook$ are averages of new COVID-19 cases during the booking period, averaging across the sixty-day time horizon may have attenuated any effect that new COVID-19 cases have on flight-level price dispersion. However, the positive and statistically significant coefficient on $CovidDestBook$ in columns (1) and (4) of Table 2 may be reflective of a composition effect among travelers.

For example, when there is an increase in $CovidDestBook$, the number of leisure travelers likely decreases more significantly than the number of business travelers. Hence, all else equal, this results in greater intertemporal price discrimination (and higher price dispersion).

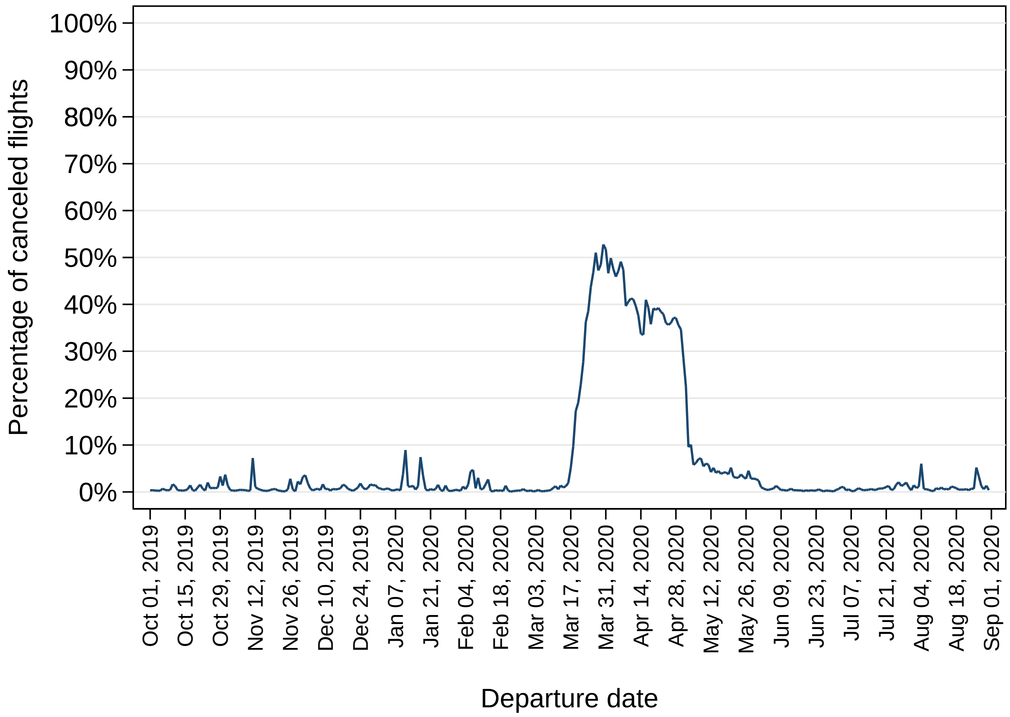
6 Robustness: Impact of Flight Cancellations

Figure 5 displays the percentage of canceled flights in the U.S. domestic market during our sample period (as reported in the Airline On-Time Performance Statistics database). As the pandemic surges, the percentage of canceled flights spikes to slightly above 50% in the middle of March 2020. Cancellation rates remain at abnormally high levels between the middle of March and late May 2020. Then, from late-May 2020 onwards, cancellation rates returned to levels observed prior to the pandemic. Specifically, the mean cancellation rate was: 0.97% before March 13$^{\text{th}}$, 2020 (the date when COVID-19 was declared a national emergency in the U.S.); 23.92% between March 13$^{\text{th}}$ and May 31$^{\text{st}}$, 2020; and 0.79% from June 1$^{\text{st}}$, 2020 through the end of our sample.

The primary threat to identification stemming from cancellations is that our dependent variables may be measured with error that is non-random, and this measurement error may result in coefficient estimates that are biased. For example, when flights are canceled late in the booking period, a shorter fare series comprised mostly of low fares is used to compute our measures of price dispersion (i.e., higher fares that are typical close to departure are not observed). Failure to observe fares close to departure is likely more of an issue in the price dispersion regressions than in the intertemporal pricing regressions because the lack of more expensive fares late in the booking period will systemically imply lower price dispersion for those flights.

In the price dispersion model described by equation (2), measurement error that results from canceled flights will be absorbed by the error term ν. Because the volume of canceled flights spikes during the pandemic, ν is positively correlated with the regressors accounting

Figure 5: Percentage of canceled flights in the U.S. domestic market (October 2019-September 2020)



for the spread of COVID-19 (i.e., $CovidOriginBook$ and $CovidDestBook$). This positive correlation implies that the coefficients on $CovidOriginBook$ and $CovidDestBook$ may be biased downward.[32]

To investigate the impact that canceled flights may have on our price dispersion results, we perform a robustness check by estimating a series of "donut" regressions that exclude the time period characterized by the abnormally high rate of flight cancellations. As demonstrated in Figure 5, this period ranges from March 13$^{\text{th}}$, 2020 to May 31$^{\text{st}}$, 2020.

The results from this "donut" specification are reported in Table 3. Note that because

[32]To determine the sign of this potential bias, consider $CovidDestBook$ (the same argument applies to $CovidOriginBook$). Decompose the error term ν into $\psi \cdot CanceledFlights + \epsilon$, with ϵ uncorrelated with $CovidDestBook$. Totally differentiating equation (2) with respect to $CovidDestBook$ yields: $\frac{\partial PriceDisp}{\partial CovidDestBook} = \beta + \psi \cdot \frac{\partial CanceledFlights}{\partial CovidDestBook}$. Note that $\frac{\partial CanceledFlights}{\partial CovidDestBook}$ is greater than zero, because an increase in COVID-19 cases in the destination market increases the likelihood that flights to that market are canceled. In contrast, ψ is less than zero, because the lack of more expensive fares late in the booking period implies lower price dispersion. As a result, the term $\psi \cdot \frac{\partial CanceledFlights}{\partial CovidDestBook}$ is negative, indicating that the coefficient on $CovidDestBook$ is biased downward.

we exclude flights departing in the period from March 13th, 2020 to May 31st, 2020, $\mathbb{1}_1$*(Dep. Mar13-May12)* disappears from the regressions, whereas $\mathbb{1}_2$*(Dep. after May12)* is renamed $\mathbb{1}$*(Dep. after May31)*. Overall, results from this robustness check are qualitatively consistent with those reported in Table 2. In particular, the negative and statistically significant coefficient on $\mathbb{1}$*(Dep. after May31)* in all Table 3 columns indicates that price dispersion decreased during the pandemic. Furthermore, consistent with the downward bias discussed in footnote 32, the coefficients on *CovidOriginBook* and *CovidDestBook* in Table 3 are larger than the corresponding baseline estimates in Table 2.

Table 3: Price dispersion results: donut regressions

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	$Gini^{lodd}$	$Gini30^{lodd}$	$Gini20^{lodd}$	ln(CV)	$\ln(P_{max}-P_{min})$
Estimator:	FE-2SLS	FE-2SLS	FE-2SLS	FE-2SLS	FE-2SLS
MktShare	2.211***	-0.152	-0.785	1.920***	0.500
	(0.736)	(0.632)	(0.600)	(0.686)	(0.307)
HHI	2.535**	4.013**	3.749**	2.527***	-0.106
	(0.994)	(1.872)	(1.697)	(0.912)	(0.429)
Holiday	-0.066***	-0.148***	-0.161***	-0.092***	0.046***
	(0.020)	(0.030)	(0.030)	(0.020)	(0.010)
Weekend	-0.065***	-0.115***	-0.115***	-0.073***	0.027***
	(0.010)	(0.015)	(0.015)	(0.010)	(0.007)
$\mathbb{1}$(Dep. after May31)	-0.955***	-0.374*	-0.482**	-0.885***	-1.254***
	(0.126)	(0.209)	(0.192)	(0.118)	(0.120)
CovidOriginBook	0.020	0.016	0.038*	0.017	0.006
	(0.024)	(0.022)	(0.021)	(0.022)	(0.013)
CovidDestBook	0.042***	0.009	0.027*	0.037***	0.027***
	(0.015)	(0.015)	(0.016)	(0.014)	(0.010)
R^2	0.039	0.004	0.005	0.042	0.133
Observations	578,340	447,267	409,554	578,340	578,340
K-P LM statistic	21.013***	8.566**	8.251**	21.013***	21.013***
K-P Wald F statistic	6.992	2.394	2.252	6.992	6.992

Notes: The sample period excludes flights that depart between March 13th, 2020 and May 31st, 2020. All specifications include flight-code fixed effects that control for any flight-code-invariant characteristics that do not differ across departure dates (e.g., route, operating carrier, and time-of-departure). Constant is included but not reported. Standard errors are clustered at the route-level. *MktShr* and *HHI* are treated as endogenous variables and instrumented for using past-year values of *MktShr* and *HHI* 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. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

7 Conclusion

In this article, we documented how the economic downturn 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 first five 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. Furthermore, we find that flight-level price dispersion decreased during the pandemic.

Notably, our findings are consistent with the theoretical predictions arising from models of intertemporal price discrimination and stochastic peak-load pricing. In the intertemporal pricing model, the decline in the share of business travel during the pandemic resulted in airlines adjusting their intertemporal price discrimination strategy by decreasing the rate at which fares increased for late-booking passengers, resulting in lower price dispersion. In the stochastic peak-load pricing model, the drastic decline in business travel demand during the pandemic decreased the shadow cost of capacity, resulting in lower fares, lower increases in fares, and thus, lower price dispersion.

The analysis presented in this article offers some fruitful 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. In particular, the decline in business travel and the movement of conferences to online formats have likely caused similar impacts on prices and price dispersion in the hospitality industry.

Future work could also extend the present analysis to airline markets in other regions. In particular, it may be important to investigate whether specific features of a local market affect the results. For example, in Europe, the expansion of high-speed rail creates intermodal competition that may affect airline prices (Bergantino and Capozza, 2015b; Bergantino et al., 2018). Future research could also examine whether strategic interactions among airlines (e.g., alliances or leader-follower behavior) have changed as a result of the pandemic (Bergantino et al., 2018; Kim et al., 2021).

Finally, another question that remains unanswered is how airlines will adjust to the potential permanent decline in business travel. As society gets more accustomed to online meetings, the demand for business travel is likely to fall. At the same time, the continued adoption of online communication tools (e.g., Microsoft Teams, Zoom, etc.) provides additional opportunities to get in touch with new commercial partners who may eventually demand face-to-face meetings. Furthermore, the broader acceptance of remote work allows a larger share of professionals to travel and work from a variety of attractive destinations. Such digital nomadism may disproportionately affect air travel to a specific subset of desired destinations. Understanding which of these potential factors dominates or how they interact with one another would provide airline managers with relevant information that will help them choose the most optimal route network and implement the most appropriate pricing strategy in the post-COVID-19 era.

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Appendix A: Supplementary Tables

Table A1: Descriptive Statistics and brief description of the variables included in the analysis

Intertemporal pricing regressions: Equation (1)

Variables	Description	Mean	Std. Dev.	Min	Max	Obs.
Fare	One-way airline fare, in U.S.$	167.2	132.6	11.00	6,155	43,160,581
DaysToDeparture 1-2	Dummy=1 if DaysToDeparture $\in [1,2]$	0.031	0.173	0.000	1.000	43,160,581
DaysToDeparture 3-6	Dummy=1 if DaysToDeparture $\in [3,6]$	0.063	0.243	0.000	1.000	43,160,581
DaysToDeparture 7-13	Dummy=1 if DaysToDeparture $\in [7,13]$	0.110	0.312	0.000	1.000	43,160,581
DaysToDeparture 14-20	Dummy=1 if DaysToDeparture $\in [14,20]$	0.109	0.312	0.000	1.000	43,160,581
DaysToDeparture 21-60	Dummy=1 if DaysToDeparture $\in [21,60]$, omitted category in the regressions	0.687	0.464	0.000	1.000	43,160,581
CovidOutbreak	Dummy=1 if fare collection is after March 13th, 2020	0.348	0.476	0.000	1.000	43,160,581
CovidOrigin	7-day moving average of new positive COVID-19 cases (in 1,000s) in the state of the origin airport	0.658	1.692	0.000	11.93	43,160,581
CovidDest	7-day moving average of new positive COVID-19 cases (in 1,000s) in the state of the destination airport	0.753	1.927	0.000	11.93	43,160,581
LCC	Dummy=1 if airline is low-cost	0.192	0.394	0.000	1.000	43,160,581
CovidOutbreak × LCC	Interaction of CovidOutbreak with LCC	0.061	0.239	0.000	1.000	43,160,581

Price dispersion regressions: Equation (2)

Variables		Mean	Std. Dev.	Min	Max	Obs.
$Gini^{lodd}$	Flight-level Gini log-odds ratio of prices, $ln[Gini/(1-Gini)]$	-1.913	0.959	-8.638	1.267	787,994
$Gini30^{lodd}$	Flight-level Gini log-odds ratio of prices collected on the last 30 days to departure	-1.658	0.769	-8.536	1.289	569,272
$Gini20^{lodd}$	Flight-level Gini log-odds ratio of prices collected on the last 20 days to departure	-1.698	0.711	-8.661	1.348	499,726
CV	Flight-level coefficient of variation, ratio of the standard deviation to the mean of the price distribution	0.358	0.241	0.001	3.401	787,994
$P_{max}-P_{min}$	Flight-level difference between the max and min price of the price distribution	199.2	205.0	1.000	4087	787,994
MktShare	Airline's market share, obtained with the number of daily nonstop flights on the route	0.317	0.281	0.000	1.000	787,994
HHI	Route Herfindhal index, $\sum_{a=1}^{n} \text{MktShare}_a^2$	0.382	0.346	0.001	1.000	787,994
Holiday	Dummy=1 if the flight departs during holiday	0.031	0.173	0.000	1.000	787,994
Weekend	Dummy=1 if the flight departs on a weekend	0.270	0.444	0.000	1.000	787,994
$\mathbb{1}_1$(Dep. Mar13-May12)	Dummy=1 if the flight departs between March 13th, 2020 and May 12th, 2020	0.196	0.397	0.000	1.000	787,994
$\mathbb{1}_2$(Dep. after May12)	Dummy=1 if the flight departs after May 12th, 2020	0.342	0.474	0.000	1.000	787,994
CovidOriginBook	Mean new positive COVID-19 cases (in 1,000s), across the 60-day booking period, in the state of the origin airport	0.848	1.728	0.000	11.29	787,994
CovidDestBook	Mean new positive COVID-19 cases (in 1,000s), across the 60-day booking period, in the state of the destination airport	0.946	1.959	0.000	11.62	787,994
Instruments						
Past-year MktShare	Past-year value of MktShare	0.295	0.255	0.000	1.000	787,994
Past-year HHI	Past-year value of HHI	0.299	0.292	0.001	1.000	787,994
Fuel price	Daily jet fuel price, U.S.$ per gallon	1.273	0.482	0.407	1.980	787,994
Fuel price × Distance	Interaction of daily jet fuel price with route distance (in 100s of miles)	14.84	10.78	0.961	53.54	787,994

Table A2: First-stage estimates for Table 2

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	MktShare	HHI	MktShare	HHI	MktShare	HHI
Past-year MktShare	0.488***	-0.359***	0.395***	-0.156***	0.346***	-0.070
	(0.033)	(0.056)	(0.026)	(0.050)	(0.022)	(0.044)
Past-year HHI	-0.006***	0.019**	-0.003*	0.022**	-0.002*	0.019**
	(0.002)	(0.009)	(0.001)	(0.009)	(0.001)	(0.008)
Fuel price	-0.034**	-0.110***	-0.021*	-0.061***	-0.015*	-0.032**
	(0.014)	(0.024)	(0.012)	(0.018)	(0.009)	(0.012)
Fuel price $\times$ Distance	-0.001	-0.003	-0.001	-0.002	-0.000	-0.002
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Holiday	0.006***	-0.005	0.007***	-0.003	0.007***	-0.004
	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)
Weekend	0.001*	-0.001	0.002***	-0.001	0.002***	-0.001
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
$\mathbb{1}_1$(Dep. Mar13-May12)	0.005	0.003	0.012***	0.018**	0.013***	0.020**
	(0.004)	(0.009)	(0.004)	(0.008)	(0.003)	(0.008)
$\mathbb{1}_2$(Dep. after May12)	0.009*	-0.003	0.012**	-0.010	0.014***	-0.005
	(0.005)	(0.011)	(0.005)	(0.011)	(0.005)	(0.011)
CovidOriginBook	0.004*	0.011**	0.006	0.014**	0.004	0.011**
	(0.002)	(0.004)	(0.003)	(0.006)	(0.003)	(0.005)
CovidDestBook	0.003*	0.009**	0.004	0.011**	0.002	0.008
	(0.002)	(0.004)	(0.003)	(0.005)	(0.003)	(0.005)
R^2	0.074	0.024	0.058	0.012	0.050	0.006
Observations	787,994	787,994	569,272	569,272	499,726	499,726

Notes: Due to varying sample sizes, columns (1) and (2) apply when $\text{Gini}^{\text{lodd}}$, ln(CV), or $\ln(P_{\max}-P_{\min})$ are the dependent variables; columns (3) and (4) apply when $\text{Gini30}^{\text{lodd}}$ is the dependent variable; columns (5) and (6) apply when $\text{Gini20}^{\text{lodd}}$ is the dependent variable. All specifications include flight-code fixed effects that control for any flight-code-invariant characteristics that do not differ across departure dates (e.g., route, operating carrier, and time-of-departure). 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.