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

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Abstract

This study provides empirical evidence documenting how COVID-19 affects intertemporal pricing and price dispersion in the U.S. domestic airline market. Studying 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 relative to the five months that immediately preceded the pandemic. We also find that flight-level prices 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 and intertemporal price discrimination.

JEL classification: L11, L93, D40, I19.

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

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1 Introduction

This paper studies the pricing of airline tickets during the COVID-19 pandemic and finds patterns that are consistent with the theoretical predictions arising from models of intertemporal price discrimination and stochastic peak-load pricing. 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). Due to the drastic decline in the demand for business travel during the pandemic, the mix of traveling passengers was more homogeneous and comprised of a larger proportion of leisure travelers.[1] 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 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 intertemporal price discrimination and price dispersion, we exploit a unique panel of over 43 million fares. Flights in our sample depart

[1] 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`. Reports by the International Air Transport Association and the World Travel & Tourism Council further confirm that business travel was more significantly impacted than leisure travel due to increased workforce flexibility, swift adjustments to corporate travel policies, and limited air connectivity (de Juniac, 2020; WTTC, 2021). "Globally, leisure spending decreased by 49 percent, and business spending decreased by 61 percent from 2019 to 2020" (WTTC, 2021).

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 United States (U.S.) and over five months of data during the national emergency.[2] 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 in addition to changes in stay-at-home orders and quarantine policies during a flight's booking period affect both prices and price dispersion.[3]

We have five main findings. Foremost, as COVID-19 spread across the country, airlines responded by discounting fares by an average of 57% in the first five months of the pandemic relative to the five months that immediately preceded the pandemic.[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. Fourth, we find that mandates requiring travelers to quarantine upon arrival decreases fares by an average of 7.2%. Fifth, we find that flight-level price dispersion decreased during the pandemic. As 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 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

[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] The closest recent paper to ours is Morlotti and Redondi (2023), who find that fares for European flights to and from Italy decreased by 31% per kilometer as a result of the COVID-19 pandemic. In contrast to Morlotti and Redondi (2023), we analyze a larger market and our richer dataset allows us to examine how stay-at-home orders, quarantine mandates, and COVID-19 infection rates at the origin and destination affect price levels and price dispersion. We also link our findings to the theoretical predictions arising from models of stochastic peak-load pricing and intertemporal price discrimination.

[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`.

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, an increase in new cases at the destination decreases fares while new cases at the origin has no statistically measurable effect. We believe these findings are reasonable. Since shutdowns and other pandemic restrictions are highly correlated with the local number of COVID-19 cases, travelers 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, and other attractions are closed due to local pandemic restrictions and most business travelers do not want to travel to markets where in-person meetings are not possible due to 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 rest of this article is organized as follows. The remainder of Section 1 summarizes previous literature and how this paper relates to them. 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.

1.1 Related Literature

It is well-documented that deviations from the law of one price occur in a variety of retail markets. 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.[5] A considerable empirical and theoretical literature has developed to better understand the principal determinants of this observed price dispersion.[6] We add to this literature by examining how intertemporal price dispersion is affected by the global economic slowdown caused by the COVID-19 pandemic.

The focus of our study is the U.S. airline industry and how price dispersion is correlated with prevailing macroeconomic conditions.[7] Previous research has shown that airline price dispersion tends to move pro-cyclically with the business cycle—increasing during expansionary phases and decreasing during recessionary phases (Cornia et al., 2012). This finding suggests that the economic downturn caused by the COVID-19 pandemic is likely to result in a reduction in price dispersion. The COVID-19 recession, however, was characterized by several unprecedented features that differentiate it from prior recessions, such that the generalizability of earlier findings are debatable.

The exogenous shock that caused the COVID-19 recession was unusually broad and multifaceted, with stay-at-home orders and quarantine mandates disrupting a wide range of industries. Another unique feature was the extraordinary airline responses. In addition to adjusting capacity and flight schedules, most U.S. airlines temporarily waived cancellation and change fees—an important component of product differentiation.[8]

Although these unique features bring into question the applicability of previous research, we demonstrate in the sections that follow that the standard predictions from models of stochastic peak-load pricing and intertemporal price discrimination do an excellent job of

[5]See 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).

[6]See 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).

[7]Other studies that examine airline price dispersion include Aryal et al. (2023); Borenstein and Rose (1994); Dai et al. (2014); Dana (1999); 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).

[8]The increase in flexibility afforded to passengers purchasing tickets during the pandemic made the quality of airline tickets more homogeneous and, because of refundability, higher relative to airline tickets issued prior to the pandemic (Escobari and Jindapon, 2014).

explaining the pricing patterns that were observed in the U.S. airline industry during the first five months of the pandemic.

2 Data

2.1 Fare and Itinerary Data

Fare and itinerary data are obtained from a major online travel agency (OTA).[9] In lieu of collecting data for all possible domestic routes, data from the Department of Transportation's Airline Origin and Destination Survey (DB1B) 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.[10] 148 of these top directional airport-pairs were selected for analysis and include a mix of competitive, monopoly, duopoly, and connecting only markets. Figure 1 displays a map of these 148 markets.

To construct the 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.[11] For each route, fares for each of the next sixty travel days were collected to capture leisure travelers who purchase well in advance of the departure date and business travelers who purchase closer to the date of departure. This strategy 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 the 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

[9] Major OTAs include Expedia, Google Flights, and Kayak. Previous studies that rely on OTA data include Escobari (2009), Gaggero and Luttmann (2023), and Luttmann (2019), among others.

[10] Given this directional definition, Los Angeles (LAX)-Chicago (ORD) and Chicago (ORD)-Los Angeles (LAX) are treated as separate markets.

[11] We focus on one-way trips due to difficulties in specifying trip duration (Alderighi et al., 2022; Bilotkach et al., 2010; Escobari et al., 2019; Luttmann and Gaggero, 2024; Luttmann, 2019). Due to our focus on economy-class tickets, we do not study product differentiation across fare classes.

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

(Allegiant, Frontier, JetBlue, Spirit, and Sun Country).[12]

2.2 COVID-19 Cases, Stay-at-Home-Orders, and Quarantine Policies

From the National Center for Health Statistics (NCHS), we downloaded the daily number of new COVID-19 cases for each state in the continental U.S.[13] These daily numbers were then used to construct seven-day moving average new COVID-19 case counts for each origin and destination market in Figure 1.

Information on the timing and duration of stay-at-home orders and interstate travel re-

[12]Fare quotes for Southwest were not available on travel aggregator websites such as Google Flights at the time of our data collection. Southwest is accounted for in our empirical analysis when we construct market structure variables such as the Herfindahl-Hirschman Index.

[13]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.

strictions (i.e., quarantine mandates) were gathered from publicly available sources such as Ballotpedia, CNN, NBC News, and state government websites in addition to select peer-reviewed studies (e.g., Bergquist et al., 2020; Jacobsen and Jacobsen, 2020; Studdert et al., 2020).[14]

2.3 Market Structure Variables

The daily number of nonstop flights for each airline and route in Figure 1 were obtained from the Department of Transportation's Airline On-Time Performance database. These numbers were then used to construct airline market shares and the Herfindahl-Hirschman Index.

3 Descriptive Analysis

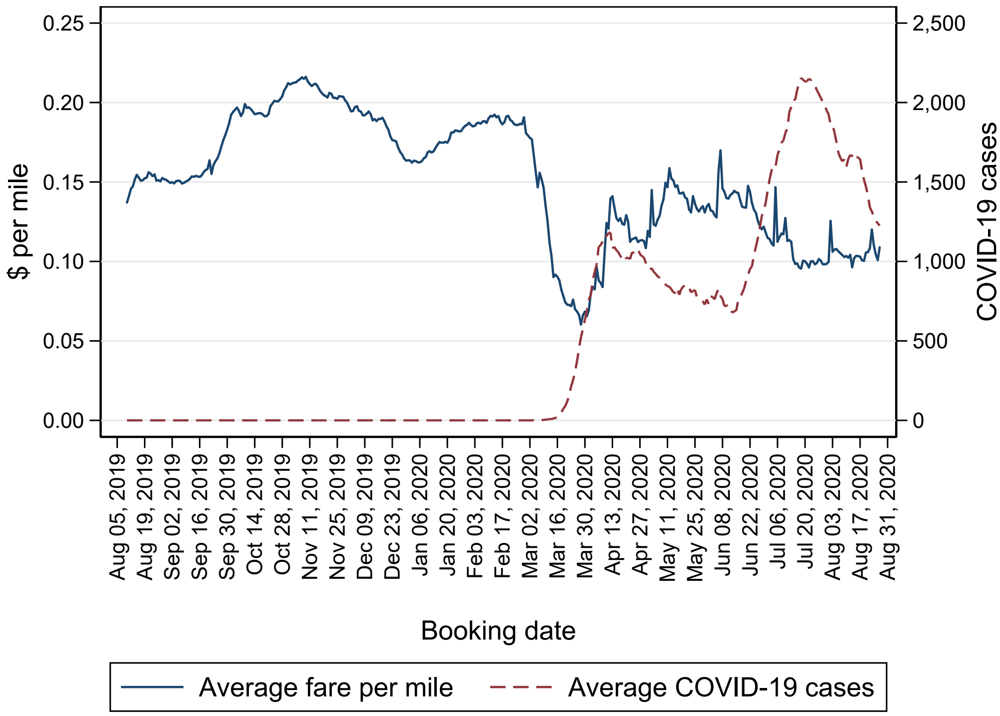
3.1 COVID-19 and Airfares

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 (*NOT* each *departure* date). The booking date is the date 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. 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, implying that pricing dynamics in Figure 2 are displayed over a time horizon of similar average length.

To relate the pricing decision of airlines to the diffusion of COVID-19, we calculated the average number of new COVID-19 cases across each state and booking date in our sample. Then, to smooth any reporting differences, we computed the seven-day moving

[14]See `https://edition.cnn.com/interactive/2020/us/states-reopen-coronavirus-trnd/`; `https://www.nbcnews.com/health/health-news/here-are-stay-home-orders-across-country-n1168736`; `https://ballotpedia.org/Travel_restrictions_issued_by_states_in_response_to_the_coronavirus_(COVID-19)_pandemic,_2020-2022`.

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



average number of new cases.[15] This moving average is displayed on the secondary Y-axis.

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. In early March 2020, fares fell substantially as the pandemic began to spread in the United States.[16] Then, as the number of new COVID-19 cases declined between May and June 2020, 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

[15]The pattern of the seven-day moving average in our sample is similar to what is observed over the entire United States. See `https://covid.cdc.gov/covid-data-tracker/#trends_dailytrendscases`.

[16]The initial fare decline occurs prior to the large increase in COVID-19 cases, suggesting that lower fares did not directly contribute to the spread of COVID-19.

fares over time.

In general, fares are lower during the pandemic months (March 2020 through August 2020). This result is particularly clear for FSCs (Panel A), but less evident for LCCs (Panel B). Since price-cost margins for LCCs are already low, LCCs likely 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.

Given that our data collection window begins sixty days prior to a flight's departure, the March and April 2020 diagrams in Figure 3 include fares collected during the pre-pandemic and pandemic periods. Although we suspect the decline in average fares observed in April 2020 and the steep increase in the last week to departure observed in March 2020 were due to the pandemic, we cannot definitively state that these changes were solely due to COVID-19.[17]

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.[18] Second, average fares across carriers mostly overlap, indicating that FSCs adopt very similar intertemporal pricing strategies.

These regularities are not observed in the May, June, and July 2020 diagrams for FSCs. In

[17]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.

[18]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 (Luttmann and Gaggero, 2024).

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

(a) Full-service carriers

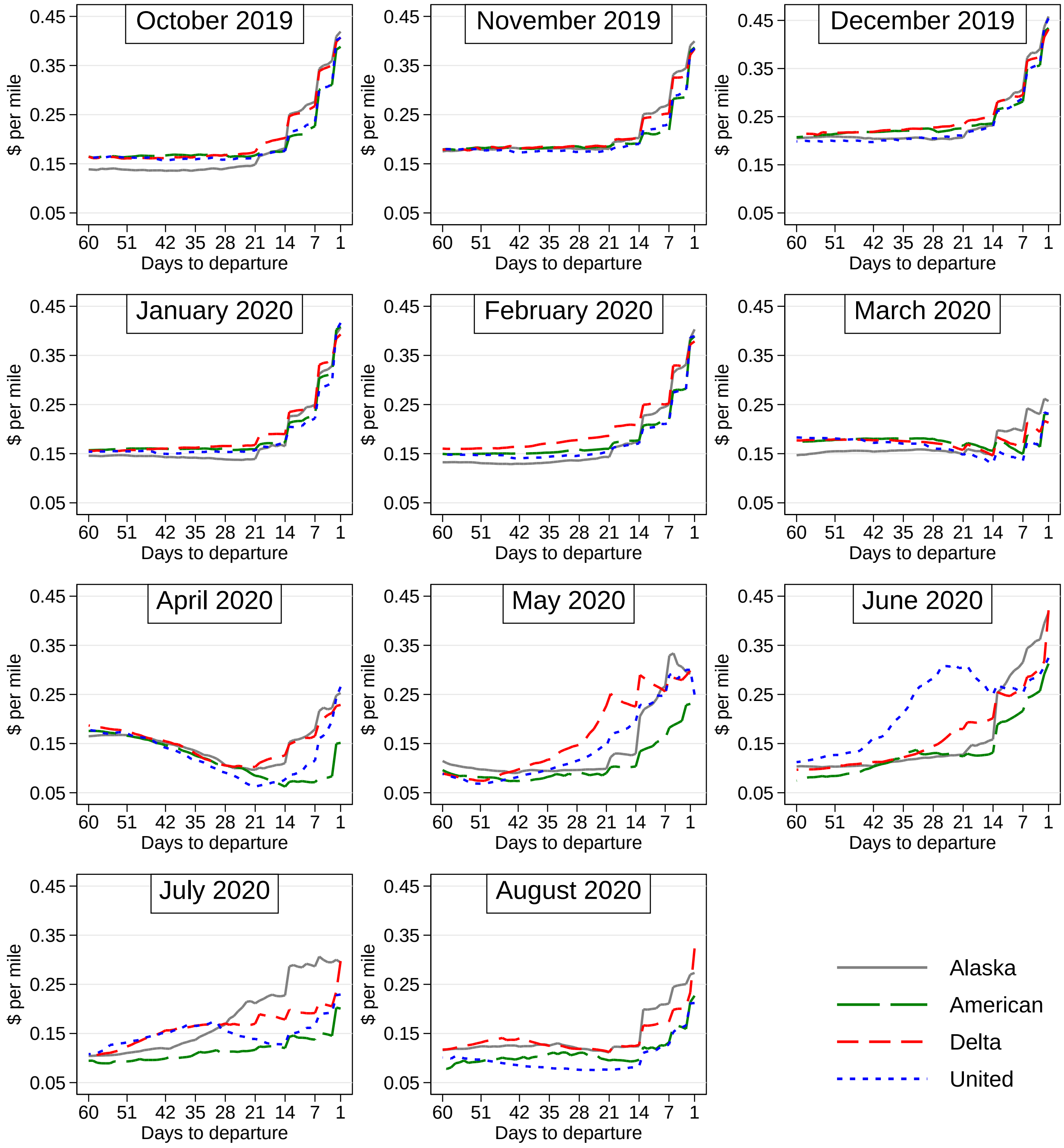
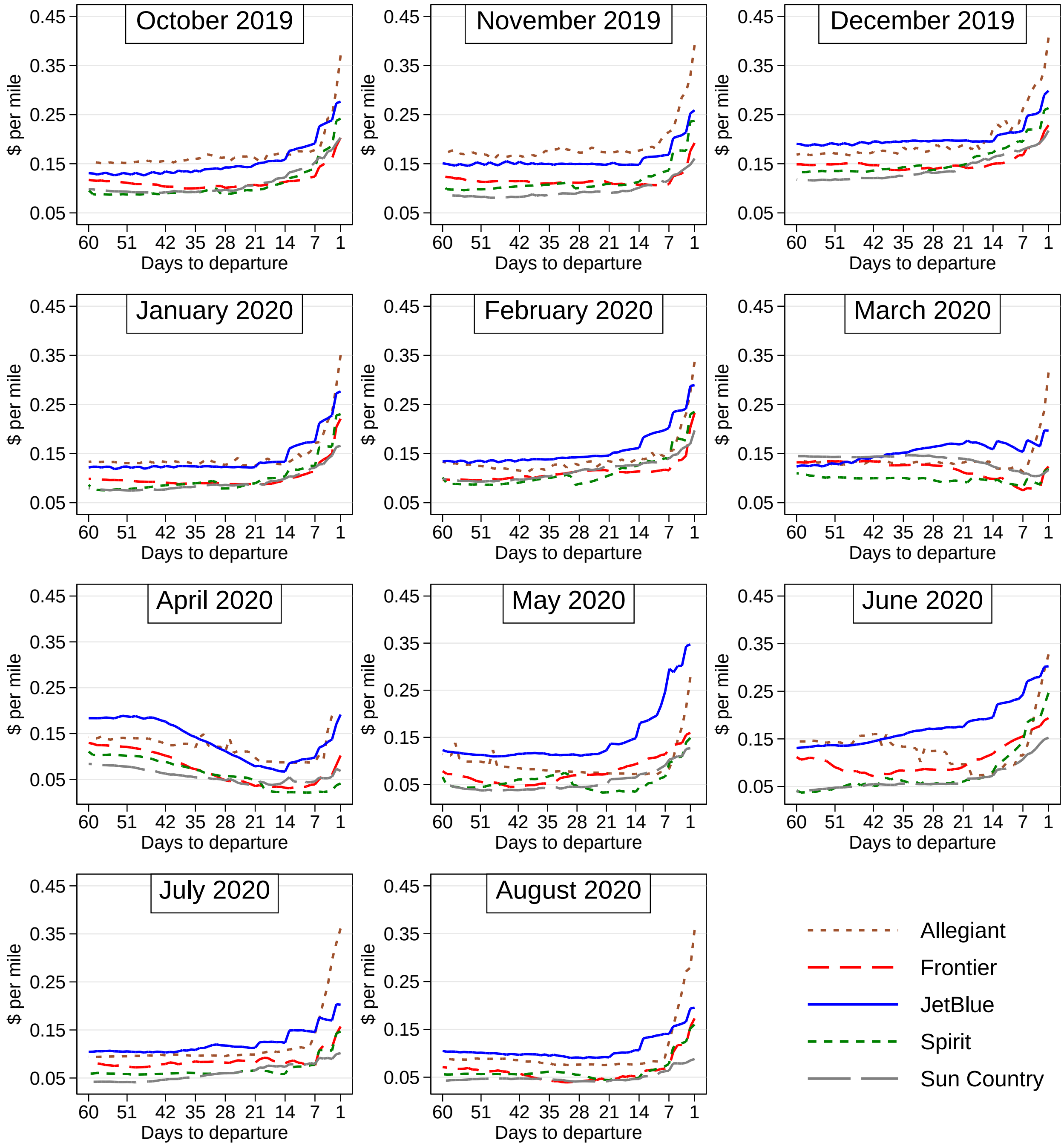


Figure 3: Average nonstop fare per mile by days to departure and month of departure (cont.)

(b) Low-cost carriers



these months, average fares do not monotonically increase as the departure date approaches. The pricing curves for each of the FSCs also do not overlap in the same manner as the pre-pandemic diagrams (e.g., compare July 2020 with October 2019 in Panel A of Figure 3). 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 pandemic. This type of behavior is expected if revenue management staff for each FSC manually intervened 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 COVID-19.[19]

A similar argument generally applies to LCCs. 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. JetBlue gradually increases fares at three weeks, two weeks, and one week prior to departure, whereas Allegiant fares are 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.

3.2 COVID-19 Policies

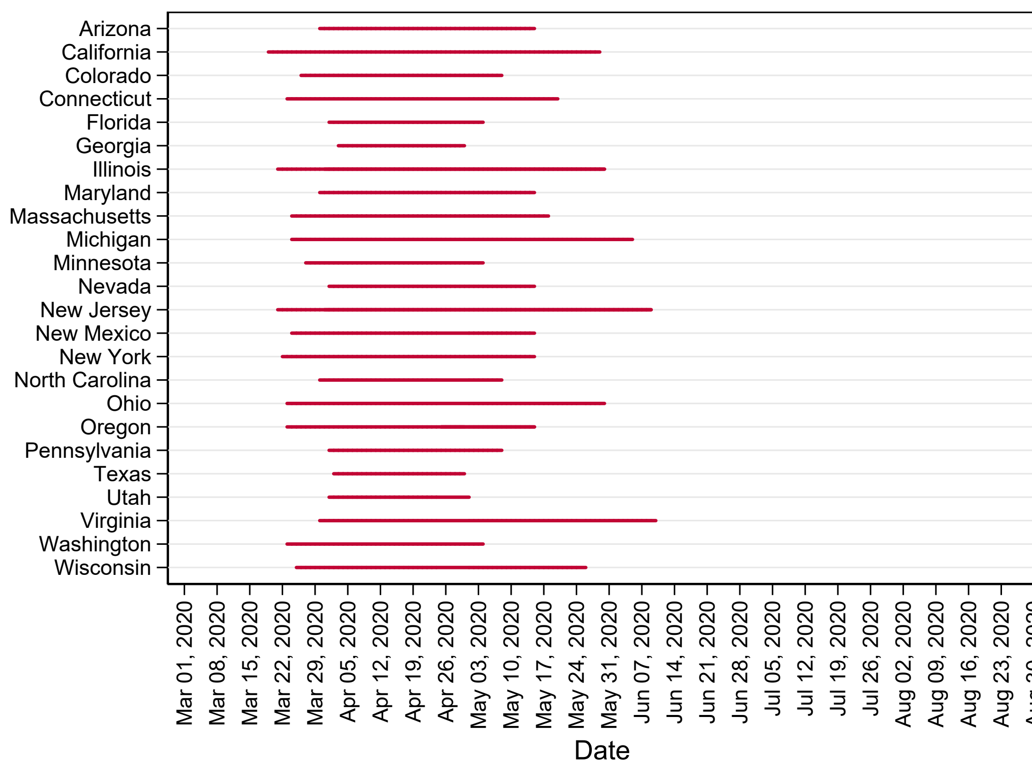
Various policies and regulations have been implemented to limit the spread of COVID-19: stay-at-home orders, vaccine mandates, face mask mandates, social distancing, work from

[19] At the Airline Group of the International Federation of Operations Research conference, Richard Cleaz-Savoyen, the Managing Director of Revenue Optimization at Air Canada, stated: "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". Sander Stomph, the Vice President at KLM, 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).

home, and travel restrictions, among others. The two primary health-related COVID-19 policies with considerable variation in timing and duration across states that we account for in our empirical analysis are stay-at-home orders and interstate quarantine mandates.

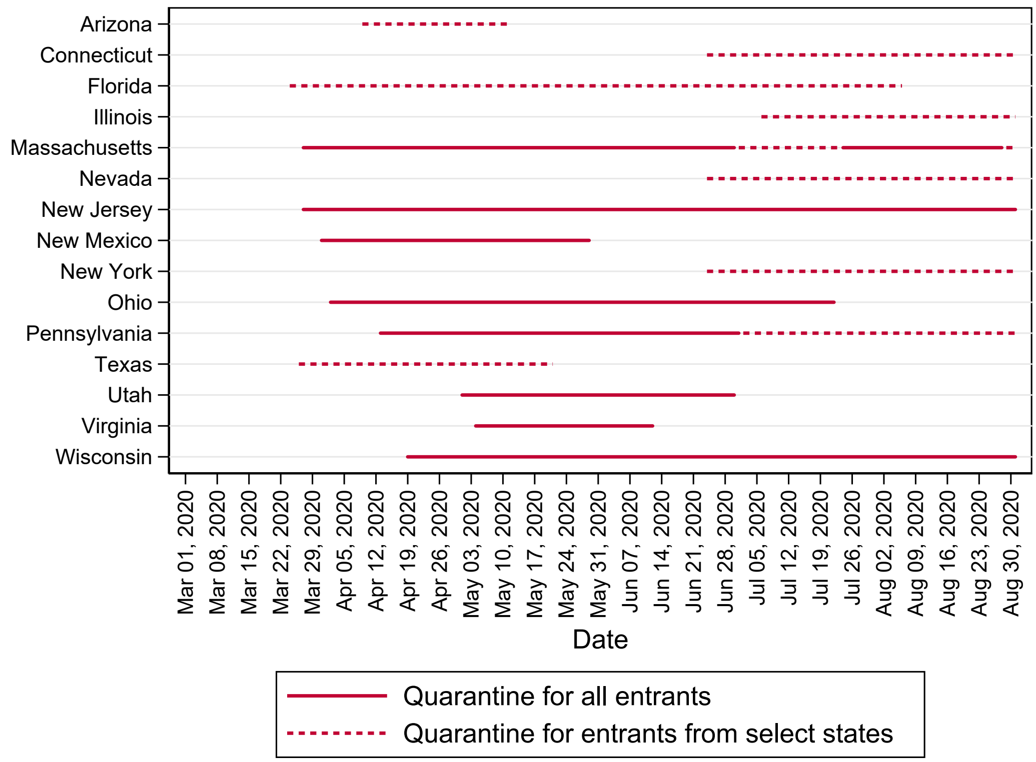
The stay-at-home order, also known as a "lockdown" or "shelter-in-place" order, required residents to remain in their homes except for essential activities (e.g., grocery shopping, walking dogs, medical care). These stay-at-home orders differed across states, with some states reluctant to implement such a policy (e.g., Georgia) whereas others implemented stay-at-home orders for a long period of time (e.g., New Jersey). By the summer of 2020, most states removed their stay-at-home orders. Figure 4 provides an overview of the timing and duration of COVID-19 stay-at-home orders for each state in our analysis sample.

Figure 4: Duration of COVID-19 stay-at-home orders by state



The quarantine mandate was a COVID-19 policy that required interstate travelers to quarantine once they reached their destination. Figure 5 reveals which states included in our sample implemented a quarantine policy and the period of time that the policy was in effect. Relative to Figure 4, the number of states is smaller because not every state in our analysis sample implemented a quarantine restriction. For example, California and Colorado did not require out-of-state travelers to quarantine during our sample period.

Figure 5: Quarantine orders restricting interstate travel



It is also worth stressing that some states issued a quarantine restriction for all interstate travelers, whereas quarantine restrictions implemented by other states applied only to travelers from select states (e.g., states where the COVID-19 infection rate was higher than a certain threshold). These quarantine mandates were often state-time varying, as the list of states subject to quarantine restrictions was generally updated on a weekly basis according to the COVID-19 infection rate of each state. For example, starting on July 6^{th}, 2020, individuals entering Chicago, IL from a COVID-19 "high-incidence" state were subject to mandatory self-quarantine.[20] Wisconsin, Missouri, North Dakota, and Nebraska were not

[20]See Section 1 of Public Health Order No. 2020-10 order: Quarantine Restrictions on Persons Entering

initially on this list, but entered the list on July 28th, 2020.[21] Similarly, if infections fell below the threshold to qualify as a high-incidence state, that state was removed from the quarantine list. For instance, Utah, which had been on the list of states since the quarantine policy was first introduced by the City of Chicago, exited the list on August 11th, 2020.[22]

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),

$$
\begin{aligned}
\log(Price_{rafdb}) \quad = \quad & \psi \cdot MktShare_{radb} + \chi \cdot HHI_{rdb} + \sum_{T=1}^{4} \delta_T \cdot DaysToDepartureT_b + \\
& + \gamma \cdot Covid_b + \sum_{T=1}^{4} \gamma_T \cdot Covid_b \times DaysToDepartureT_b + \\
& + \pi \cdot Covid_b \times LCC_a + \alpha \cdot InfectionsOrig_{rb} + \beta \cdot InfectionsDest_{rb} + \\
& + \theta \cdot StayHomeOrig_{rb} + \phi \cdot StayHomeDest_{rb} + \varphi \cdot Quarantine_{rb} + \\
& + \rho_{rafd} + \varepsilon_{rafdb} \qquad (1)
\end{aligned}
$$

where the individual dimension of the panel is the combination of directional airport-pair route r, airline a, and flight itinerary f that is scheduled to depart on a given day d.[23] The

Chicago from High Case-Rate States, issued by the Commissioner of Health of the City of Chicago, https://www.chicago.gov/city/en/sites/covid-19/home/health-orders.html. A state with a new COVID-19 case rate greater than 15 COVID-19 cases per 100,000 residents per day (7-day rolling average) was classified as a high-incidence state.

[21]See https://abc7chicago.com/chicago-quarantine-wisconsin-covid-travel-order-update/6338248/.

[22]See https://cbs2iowa.com/news/local/chicago-removes-iowa-two-other-states-from-its-emergency-travel-order.

[23]The nonstop American flight from Chicago (ORD) to Los Angeles (LAX) on April 22nd, 2020 that departs at 7:23am is an example of f. A combination of flights on the same itinerary is another example of f (e.g., the pair of Delta flights on November 15th, 2019 from Chicago (MDW) to Atlanta (ATL) and ATL to Las Vegas).

time dimension of the panel is represented by b, which records the date the fare is booked (i.e., observed), henceforth referred to as the booking date.

In this specification, the flight-date fixed-effect ρ identifies the unique combination of flight, airline, route, and departure date. This fixed effect controls for any time-invariant flight, airline, departure date, and route-specific characteristics that affect fares.

The third term on the right hand side of equation (1) are the set of booking period dummies. As suggested by Figure 3 and the analysis in Luttmann and Gaggero (2024), 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 $Covid$, *InfectionsOrig*, *InfectionsDest*, $StayHomeOrig$, $StayHomeDest$, and $Quarantine$. $Covid$ is a dummy equal to one if the booking date is after March 13$^{\text{th}}$, 2020, the date when COVID-19 was declared a national emergency in the United States. *InfectionsOrig* (*InfectionsDest*) is the 7-day moving average of new positive COVID-19 cases in thousands in the state of the origin (destination) airport on the booking date. 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. $StayHomeOrig$ ($StayHomeDest$) is a dummy that equals one if a stay-at-home order is in effect in the origin (destination) state on the booking date. $Quarantine$ is a dummy that equals one if the destination state requires travelers coming from the origin state to quarantine on the booking date.

The variable $Covid \times LCC$ interacts $Covid$ with a low-cost carrier indicator to test whether the impact of the pandemic on fares differs by carrier type.

$MktShare$ is airline a's market share on route r and booking date b, computed using the daily number of nonstop flights on the route that were for sale on booking date b. HHI is the Herfindahl-Hirschman Index for route r on booking date b. Under normal circumstances, $MktShare$ and HHI would be absorbed by the flight-date fixed effects since they would not vary during a flight's booking period. During the pandemic, airlines were frequently rescheduling and canceling flights to meet the drastic drop of demand, resulting in competition that varies during a flight's booking period.

The inclusion of $MktShare$ and HHI raises the concern of simultaneity bias.[24] To correct for this potential endogeneity, we adopt a two-stage least squares (2SLS) approach. Because the flight-date fixed effects capture factors that are time-invariant during the booking period, the instrumental variables we employ must vary during the booking period of a given flight.

Our first instrument is the 5-week lag of airline a's market share at the same number of days to departure as the observed flight, computed using airline a's number of flights scheduled five weeks before the observed flight on the same route. As an example, consider a Delta flight from JFK to LAX departing on June 30$^{\text{th}}$, 2020 observed at ten days to departure (i.e., on June 20$^{\text{th}}$, 2020). The instrument we construct is Delta's market share on the JFK-LAX route obtained using all JFK-LAX flights that are scheduled to depart five weeks before June 30$^{\text{th}}$, 2020 (i.e., on May 26$^{\text{th}}$, 2020) that are for sale at ten days to departure (i.e., on May 16$^{\text{th}}$, 2020). Our second instrument is the five-week lag of HHI at the same number of days to departure as the observed flight, constructed using the aforementioned 5-week lag of market shares.

The validity of these instruments relies on the fact that COVID-19 waves lose momentum several weeks after the start of each wave due to increased immunity and fewer potential hosts to infect (Swain and Wallentin, 2024). The five-week lag also allows us to sample flights on similar market conditions such as the same day of the week and approximate season (Alderighi et al., 2015b, 2022; Bilotkach et al., 2015). While previous market structure is certainly correlated with current market structure, these two instruments are only valid if

[24]Simultaneity bias is likely minimal in our context because airlines' cancellation and rescheduling behavior was so dynamic and unpredictable during the pandemic that the revenue management office of each airline likely ignored the behavior of its competitors. Gayle and Wu (2013) demonstrate that accounting for endogenous carrier entry using a structural model has a negligible impact on fares in a subsequent regression, suggesting that simultaneity bias is not a major concern.

unobserved cost and demand shocks that apply to the current period are not correlated with the unobserved cost and demand shocks that occurred five-weeks prior (Evans et al., 1993).[25]

The variables of interest in equation (1) are the set of interactions between *Covid* 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. According to the predictions from the intertemporal pricing model, the decline in the share of business travel during the COVID-19 pandemic should decrease the rate at which fares increase for late-booking passengers. Hence, the coefficients on these interaction terms are expected to be negative, especially in the last week to departure.

Finally, equation (1) is estimated using 2SLS 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 equation (1). The first column includes only the market structure variables, *DaysToDeparture* dummies, and flight-date fixed effects and confirms the well-documented empirical result that fares increase as the flight's departure date approaches.[26] For example, the coefficient of 0.676 on *DaysToDeparture 1-2* indicates that flights booked in the last two days before departure are, on average, 97% higher than comparable flights booked 21 to 60 days before departure.[27]

[25] As a robustness check, we report ordinary least squares estimates in Appendix Table A.4.

[26] See Alderighi et al. (2015a); Avogadro et al. (2021); Bergantino and Capozza (2015a); Escobari (2012, 2014); Escobari and Jindapon (2014); Gaggero and Piga (2010); Gaggero and Luttmann (2023).

[27] The marginal effect is $(e^{0.676} - 1)\% = 96.6\%$.

Table 1: Intertemporal pricing results

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	ln(Price)	ln(Price)	ln(Price)	ln(Price)	ln(Price)
MktShare	-0.060	-0.197	-0.044	-0.172	-0.164
	(0.280)	(0.274)	(0.257)	(0.267)	(0.268)
HHI	0.370***	0.337***	0.237***	0.322***	0.319***
	(0.110)	(0.100)	(0.082)	(0.093)	(0.093)
DaysToDeparture 1-2	0.676***	0.754***	0.754***	0.805***	0.805***
	(0.019)	(0.018)	(0.019)	(0.022)	(0.022)
DaysToDeparture 3-6	0.442***	0.516***	0.515***	0.542***	0.542***
	(0.023)	(0.022)	(0.023)	(0.027)	(0.027)
DaysToDeparture 7-13	0.214***	0.275***	0.276***	0.274***	0.274***
	(0.020)	(0.018)	(0.019)	(0.020)	(0.020)
DaysToDeparture 14-20	0.020**	0.067***	0.067***	0.073***	0.073***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Covid		-0.837***		-0.793***	-0.731***
		(0.029)		(0.030)	(0.031)
Covid × LCCs					-0.285***
					(0.048)
BookingMarch2020			-0.607***		
			(0.018)		
BookingApril2020			-0.566***		
			(0.031)		
BookingMay2020			-0.390***		
			(0.035)		
BookingJune2020			-0.306***		
			(0.040)		
BookingJuly2020			-0.470***		
			(0.044)		
BookingAugust2020			-0.437***		
			(0.052)		
Covid × DaysToDep. 1-2				-0.145***	-0.146***
				(0.022)	(0.022)
Covid × DaysToDep. 3-6				-0.076***	-0.077***
				(0.024)	(0.024)
Covid × DaysToDep. 7-13				0.001	0.001
				(0.016)	(0.016)
Covid × DaysToDep. 14-20				-0.018**	-0.018**
				(0.008)	(0.008)
InfectionsOrig				0.003	0.004
				(0.005)	(0.005)
InfectionsDest				-0.019***	-0.019***
				(0.004)	(0.004)
StayHomeOrig				-0.057***	-0.059***
				(0.017)	(0.017)
StayHomeDest				0.010	0.004
				(0.017)	(0.017)
Quarantine				-0.075***	-0.071***
				(0.026)	(0.025)
Kleibergen-Paap χ^2 Stat.	36.926***	36.952***	37.265***	37.670***	37.628***
Kleibergen-Paap Wald F Stat.	33.346***	33.456***	33.504***	33.617***	33.575***
Adjusted R^2	0.133	0.269	0.227	0.274	0.276
Observations	42,801,983	42,801,983	42,801,983	42,801,983	42,801,983

Notes: $MktShr$ and HHI are treated as endogenous variables and instrumented for using five-week lags of $MktShr$ and HHI on the same route and same number of days to departure as the observed flight. First-stage estimates are reported in Appendix Tables A.2 and A.3. Summary statistics are provided in Appendix Table A.1. 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. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

To provide a baseline for how fare levels differ across the pre-pandemic and pandemic periods of our sample, column 2 adds the *Covid* dummy to the specification in column 1. The Adjusted R^2 doubles, illustrating the importance of *Covid* for explaining pandemic fares. The coefficient of -0.837 on *Covid* indicates that domestic fares for flights departing in the five-month period after COVID-19 was declared a national emergency were, on average, 57% cheaper than comparable fares for flights departing in the five-month period immediately preceding the emergency.

Column 3 replaces the *Covid* variable with six monthly dummies, one for each month since COVID-19 was declared a national emergency. The omitted group is the seven-month booking period prior to COVID-19 being declared a national emergency. The negative coefficients on these six monthly dummies confirm that the pandemic had a negative impact on fares. Consistent with the descriptive analysis in Section 3, the magnitude of the coefficients demonstrate that the negative effect of the pandemic on fares was largest in the very early stages (March and April 2020) when stay-at-home and quarantine mandates were first introduced.[28]

Column 4 adds the set of interactions between *Covid* and the $DaysToDeparture$ dummies to the specification in column 2. Consistent with the predictions from the intertemporal pricing model, 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.[29] This rate slowdown is especially evident in the last week to departure.[30]

To examine how heterogeneity in the diffusion of COVID-19 affects fares, column 4 also includes the 7-day moving average number of new positive COVID-19 cases in the origin

[28] We conducted a placebo test by including February 2020, and then January and February 2020 among the set of monthly dummies. The coefficients on these pre-pandemic dummies are positive and statistically significant, confirming that the structural break occurred in March 2020 (see Appendix Table A.5).

[29] The statistically insignificant coefficient on *Covid* × *DaysToDeparture 7-13* suggests that the slower rate of intertemporal fare hikes 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 FSCs during the pandemic months (e.g., Alaska in May-August 2020 or American and Delta in June 2020).

[30] As illustrated in Panel B of Figure 3, this result may be driven by LCCs who did not substantially increase fares in the last week to departure during the pandemic months of our sample.

(*InfectionsOrig*) and destination (*InfectionsDest*) states, indicators if a stay-at-home order was in place in the origin (*StayHomeOrig*) and destination (*StayHomeDest*) states, and an indicator if a quarantine mandate applied to passengers traveling from the origin state to the destination state (*Quarantine*). The coefficient on *InfectionsDest* is negative and statistically significant, providing additional evidence that COVID-19 adversely affected fares. The statistically insignificant coefficient on *InfectionsOrig* implies that pandemic fare decreases are mainly driven by the diffusion of COVID-19 at the destination. This finding is consistent with the negative and statistically significant coefficient on *Quarantine* as passengers dislike traveling to destinations that require them to quarantine on arrival. The negative and statistically significant coefficient on *StayHomeOrig* and the statistically insignificant coefficient on *StayHomeDest* are also reasonable, since a stay-at-home order that is effective at the origin is likely more relevant than a stay-at-home-order at the destination because stay-at-home orders at the origin inhibit traveling anywhere, irrespective of the destination market.

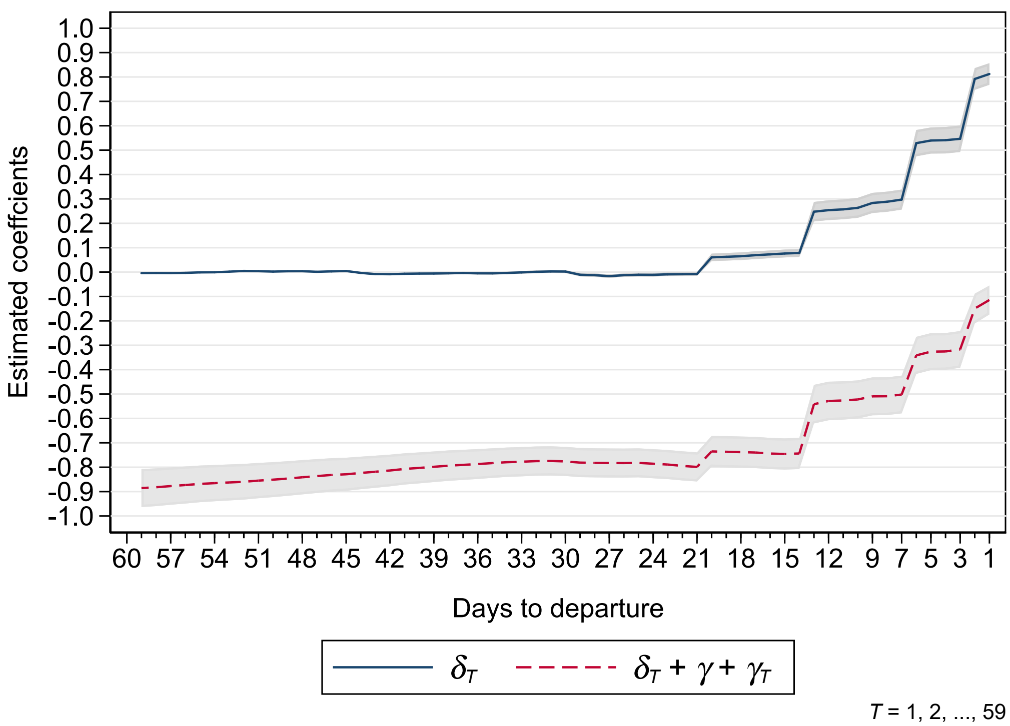
We believe these findings are rational from the passenger perspective. If the number of new COVID-19 cases at the destination are high, fares must be heavily discounted to entice prospective passengers to purchase when the likelihood of new pandemic restrictions being introduced at the destination increases. The coefficient on *InfectionsDest* 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. Similarly, a quarantine mandate that is in effect at the destination is associated with a 7.2% fare decrease.

To investigate whether pandemic pricing differed between FSCs and LCCs, column 5 adds the interaction between *Covid* and a LCC indicator. The negative and statistically significant coefficient on $Covid \times LCC$ indicates that LCC fares were on average 24.8% lower than FSC fares during the pandemic months of our sample. Relative to the pre-pandemic period, FSC fares were 51.9% lower and LCC fares 63.8% lower.

To further examine intertemporal pricing, we perform a sensitivity check on our booking period groupings by replacing the four days to departure variables with 59 mutually exclusive days to departure dummies. Results from this sensitivity are presented in Figure 6.

The solid blue line in Figure 6 plots the estimated coefficients on the 59 days to departure dummies while the dashed red line plots the linear combination of the $DaysToDeparture$ dummies and $Covid$ variables. The shaded gray area encompassing the solid blue and dashed red lines represents the 95% confidence interval. Consistent with the descriptive analysis in Section 3, the dashed red line in Figure 6 demonstrates that both fares and the rate of intertemporal price increases are lower during the pandemic months.[31] 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).[32]

Figure 6: Estimated coefficients on the daily DaysToDeparture dummies with 95% confidence interval during the pre-pandemic and pandemic periods



[31]Coefficients on the non-interacted Covid variables in this sensitivity are qualitatively similar to the coefficients reported in Table 1.

[32]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).

5 COVID-19 and Price Dispersion

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. 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,

$$\begin{aligned} PriceDisp_{rafd} = \; & \phi \cdot MktShr_{rad} + \theta \cdot HHI_{rd} + \sigma \cdot Holiday_d + \delta \cdot Weekend_d + \\ & + \gamma_1 \cdot PartialCovidBook_d + \gamma_2 \cdot FullCovidBook_d + \\ & + \alpha \cdot InfectionsOrigBook_{rd} + \beta \cdot InfectionsDestBook_{rd} + \\ & + \eta \cdot StayHomeOrigBook_{rd} + \mu \cdot StayHomeDestBook_{rd} + \\ & + \varrho \cdot QuarantineBook_{rd} + \lambda_{raf} + \nu_{rafd} \end{aligned} \quad (2)$$

where the dependent variable $PriceDisp$ stands for price dispersion, which we measure using several different metrics (Cui et al., 2019). First, consistent with previous studies of the airline industry, we measure price dispersion using the Gini log-odds ratio, $ln[Gini/(1-Gini)]$.[33] We adopt different nuances of this 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

[33] See Borenstein and Rose (1994); Gaggero and Piga (2011); Gerardi and Shapiro (2009); Kim et al. (2021).

$Gini20^{lodd}$, respectively).[34] Other measures of price dispersion employed as the dependent variable are the natural logarithm of the flight-level coefficient of variation (CV) and the natural logarithm of the flight-level price range (i.e., $P_{\max} - P_{\min}$).[35]

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 departure date for flight f. Consistent with Gaggero and Piga (2011), we refer to λ as the set of flight-code fixed effects. Since an observation 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, airline, time-of-departure).[36] In this respect, λ differs from ρ, the fixed-effect in equation (1), which identified an individual flight *and* departure date combination.

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 (2) is estimated using 2SLS. We correct for this potential endogeneity using three instruments: (i) the airline's $MktShr$ on the route on the same corresponding day during the previous year,[37] (ii) the HHI of the route on the same cor-

[34]Since Figures 3 and 6 demonstrate that fare changes are limited between 21 and 60 days before departure, $Gini30^{lodd}$ and $Gini20^{lodd}$ examine whether estimates are affected by the duration of the booking period used to compute the Gini coefficient.

[35]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).

[36]The fixed effects in equation (2) are different than those in studies that rely on quarterly data. Instead of 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. Due to unobserved factors, the 7:05am Delta flight from Atlanta to Boston (DL 327) may display a different price dispersion pattern than the 5:00pm Delta flight from Atlanta to Boston (DL 360).

[37]By "same corresponding day" we mean that observations are matched with respect to the same day-of-

responding day during the previous year, and (iii) the number of U.S. cities served nonstop by the observed airline from the destination airport of the route on the departure date. The first two instruments reflect that lagged market structure is correlated with current market structure.[38] The last instrument hinges on the idea that the number of cities that an airline serves from the endpoint airport on the route affects the marginal cost of serving that route through economies of traffic density (Berry and Jia, 2010; Brueckner and Spiller, 1994). The exogeneity of this instrument relies on the assumption that the number of cities that the airline serves from the endpoint airport on the route does not directly affect demand for that route.[39]

To control for flight-specific characteristics, we use a series of indicators. $Holiday$ equals one if the departure date of flight f falls on a holiday.[40] We expect lower fare dispersion on holidays due to systematic peak-load pricing. $Weekend$ equals 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 since business travelers typically do not fly on weekends.

The variables of interest in equation (2) are those that capture the effect of the pandemic: $PartialCovidBook$, $FullCovidBook$, *InfectionsOrigBook*, *InfectionsDestBook*, $StayHomeOrigBook$, $StayHomeDestBook$, and $QuarantineBook$. The first two regressors are indicators that specify the departure date of the flight: $PartialCovidBook$ equals one if the flight departs between March 13th, 2020 and May 12th, 2020 while $FullCovidBook$ equals one for flights de-

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.

[38]Other papers that instrument for market structure using lagged measures include Davis (2005), Evans et al. (1993), Gaggero and Luttmann (2025), Greenfield (2014), and Whalen (2007).

[39]A previous version employed jet fuel prices and the interaction of jet fuel prices with route distance as instruments. An anonymous referee correctly pointed out that jet fuel prices were directly affected by COVID-19 as a result of the drastic decline in travel demand. Although the number of routes an airline serves from the destination airport may have also been affected by COVID-19, the number of routes was likely less directly affected than jet fuel prices. For example, an airline could have reduced flight frequency on a given route without completely exiting the route.

[40]Twelve holidays occur during our sample period: Columbus Day, Veterans Day, Thanksgiving, 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.

parting after May 12$^{\text{th}}$, 2020. Because our fare collection begins sixty days prior to departure, the set of fares used to calculate price dispersion for flights indexed by $PartialCovidBook$ are collected in both the pre-pandemic and pandemic periods, whereas the set of fares used to calculate price dispersion for flights indexed by $FullCovidBook$ are collected entirely during the pandemic.

To account for the spread of COVID-19 at the origin and destination, $InfectionsOrigBook$ and $InfectionsDestBook$ 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. 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. $StayHomeOrigBook$ and $StayHomeDestBook$ are defined as the fraction of days during flight f's sixty-day booking period that a stay-at-home order was in effect in the origin and destination airport states, respectively. Finally, $QuarantineBook$ is the fraction of days during flight f's sixty-day booking period that a quarantine mandate was in effect at the destination state for passengers arriving from the origin state.

5.2 Price Dispersion Results

The results of estimating equation (2) with 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. HHI is also positive and statistically significant at conventional levels, indicating that a decrease in competition

Table 2: Price dispersion results

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	$\text{Gini}^{\text{lodd}}$	$\text{Gini30}^{\text{lodd}}$	$\text{Gini20}^{\text{lodd}}$	ln(CV)	$\ln(P_{max}-P_{min})$
Estimator:	FE-2SLS	FE-2SLS	FE-2SLS	FE-2SLS	FE-2SLS
MktShare	1.013***	0.110	0.245	0.749***	-0.079
	(0.291)	(0.225)	(0.205)	(0.233)	(0.197)
HHI	0.593**	-0.606**	-0.029	0.464**	-0.841***
	(0.282)	(0.296)	(0.298)	(0.215)	(0.199)
Holiday	-0.044***	-0.155***	-0.166***	-0.074***	0.058***
	(0.013)	(0.017)	(0.018)	(0.012)	(0.011)
Weekend	-0.022***	-0.079***	-0.078***	-0.035***	0.065***
	(0.005)	(0.008)	(0.009)	(0.005)	(0.008)
PartialCovidBook	-0.057	0.040	-0.059*	-0.154***	-0.352***
	(0.045)	(0.041)	(0.034)	(0.039)	(0.038)
FullCovidBook	-0.259***	-0.114**	-0.287***	-0.312***	-0.628***
	(0.053)	(0.052)	(0.057)	(0.045)	(0.046)
InfectionsOrigBook	-0.004	0.014	0.037***	-0.001	-0.022*
	(0.014)	(0.011)	(0.011)	(0.012)	(0.012)
InfectionsDestBook	0.025**	0.006	0.023**	0.024***	-0.001
	(0.011)	(0.010)	(0.009)	(0.008)	(0.011)
StayHomeOrigBook	-0.086	-0.049	-0.135	-0.098*	-0.189***
	(0.060)	(0.081)	(0.086)	(0.051)	(0.064)
StayHomeDestBook	-0.220***	-0.036	0.026	-0.144**	-0.108
	(0.074)	(0.067)	(0.076)	(0.061)	(0.066)
QuarantineBook	0.074	0.128	0.129	0.110*	-0.040
	(0.081)	(0.092)	(0.109)	(0.065)	(0.071)
Kleibergen-Paap χ^2 Stat.	31.434***	33.034***	26.919***	31.434***	31.434***
Kleibergen-Paap Wald F Stat.	11.757**	11.998**	8.131*	11.757**	11.757**
Hansen J Stat.	0.093	0.804	1.206	0.026	1.620
R^2	0.019	0.015	0.006	0.017	0.140
Observations	787,994	569,272	499,726	787,994	787,994

Notes: Summary statistics are provided in Appendix Table A.1. 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, 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 number of U.S. cities served nonstop by the observed airline from the destination airport on the departure date. First-stage estimates are provided in Appendix Table A.6. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

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.[41]

[41] This finding is also consistent with the results in Dai et al. (2014) and 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 less dispersed during the entire booking period for these holiday flights.[42]

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.

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 $PartialCovidBook$ and $FullCovidBook$ indicate that fares collected during the pandemic exhibit *less* price dispersion than similar fares collected prior to the pandemic. In all specifications, the absolute value of the coefficient on $FullCovidBook$ is larger than the absolute value of the coefficient on $PartialCovidBook$, indicating 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 that documented a lower rate of fare hikes in the last week to departure (see Table 1), 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. 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

[42]The data in Gaggero and Piga (2011) cover a sample of European routes. To the best of our knowledge, this paper is the first to document the holiday effect on price dispersion for the U.S. domestic market.

price dispersion.

The evidence on *InfectionsOrigBook* and *InfectionsDestBook* is mixed, with the coefficients on these variables often statistically insignificant. Since *InfectionsOrigBook* and *InfectionsDestBook* 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.

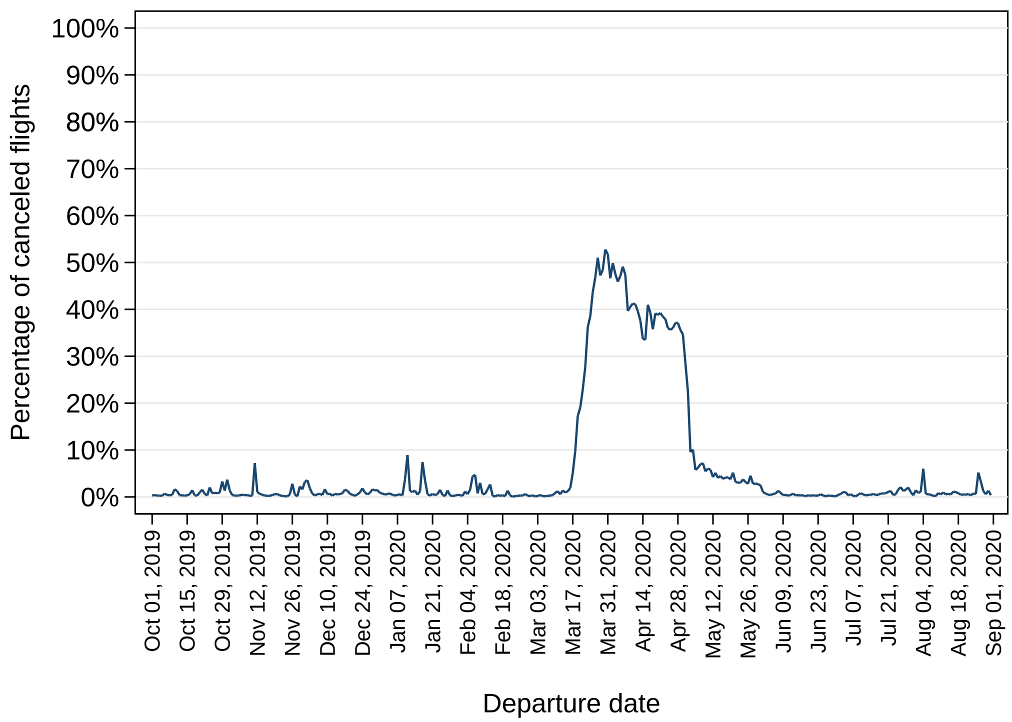
StayHomeOrigBook and *StayHomeDestBook* are generally negative and, in some instances, statistically significant, implying that stay-at-home orders reduce price dispersion. In contrast, the coefficients on *QuarantineBook* are statistically insignificant in almost all Table 2 specifications, suggesting that quarantine mandates did not affect price dispersion.

6 Robustness: Impact of Flight Cancellations

Figure 7 displays the percentage of canceled flights in the U.S. domestic market during our sample period (as reported in the Airline On-Time Performance 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 return 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. 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).

Figure 7: Percentage of canceled flights in the U.S. domestic market (October 2019-August 2020)



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.

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 7, 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. Because we exclude flights departing in the period from March 13$^{\text{th}}$, 2020 to May 31$^{\text{st}}$, 2020, $PartialCovidBook$ disappears from the regressions. Overall, results from this robustness check are qualitatively consistent with those reported in Table 2. The negative coefficient on $FullCovidBook$ in all Table 3 columns indicates that price dispersion decreased during the pandemic.

Table 3: Price dispersion results: donut regressions

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	$\text{Gini}^{\text{lodd}}$	$\text{Gini30}^{\text{lodd}}$	$\text{Gini20}^{\text{lodd}}$	ln(CV)	$\ln(\text{P}_{\text{max}}-\text{P}_{\text{min}})$
Estimator:	FE-2SLS	FE-2SLS	FE-2SLS	FE-2SLS	FE-2SLS
MktShare	1.406**	-0.012	-0.233	1.269**	1.024*
	(0.625)	(0.360)	(0.319)	(0.592)	(0.544)
HHI	1.669*	1.744***	1.344**	1.892**	1.501
	(1.010)	(0.628)	(0.556)	(0.965)	(0.986)
Holiday	-0.071***	-0.162***	-0.176***	-0.096***	0.054***
	(0.018)	(0.022)	(0.021)	(0.018)	(0.013)
Weekend	-0.068***	-0.118***	-0.118***	-0.075***	0.028***
	(0.009)	(0.012)	(0.012)	(0.009)	(0.007)
FullCovidBook	-0.528***	-0.142	-0.263	-0.520***	-1.079***
	(0.120)	(0.186)	(0.187)	(0.112)	(0.134)
InfectionsOrigBook	0.001	0.000	0.029*	-0.002	-0.017
	(0.020)	(0.015)	(0.015)	(0.017)	(0.018)
InfectionsDestBook	0.021	0.003	0.019*	0.018	-0.001
	(0.016)	(0.010)	(0.010)	(0.013)	(0.012)
StayHomeOrigBook	-0.216**	-0.204*	-0.166	-0.230***	-0.213***
	(0.084)	(0.121)	(0.124)	(0.072)	(0.081)
StayHomeDestBook	-0.329***	-0.127	-0.165	-0.264**	-0.272**
	(0.127)	(0.092)	(0.107)	(0.116)	(0.117)
QuarantineBook	0.147	0.217**	0.112	0.190**	0.027
	(0.104)	(0.103)	(0.122)	(0.096)	(0.102)
Kleibergen-Paap χ^2 Stat.	7.707**	9.374***	10.246***	7.707**	7.707**
Kleibergen-Paap Wald F Stat.	2.753	3.454	3.379	2.753	2.753
Hansen J Stat.	1.066	2.302	0.306	0.756	1.091
R^2	0.027	0.005	0.001	0.018	0.122
Observations	578,340	447,267	409,554	578,340	578,340

Notes: The analysis sample excludes flights that depart between March 13$^{\text{th}}$, 2020 and May 31$^{\text{st}}$, 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, 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 number of U.S. cities served nonstop by the observed airline from the destination airport on the departure date. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

7 Conclusion

In this paper, we documented how the economic downturn caused by the COVID-19 pandemic affected intertemporal price discrimination and price dispersion in the U.S. airline industry. Exploiting a unique panel of 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 (relative to flights departing in the five month period immediately preceding the emergency declaration). 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. Policies requiring travelers to quarantine upon arrival were also found to decrease fares by an average of 7.2%. Finally, we find that flight-level price dispersion decreased during the pandemic.

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 lower price dispersion.

The analysis presented in this paper 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 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.

Because the analysis in this paper focused on one-way tickets, future work could also examine how adding roundtrip tickets to the analysis impacts results. If one-way tickets are more appealing to business travelers, then the decrease in the rate of intertemporal price discrimination that we observed during the pandemic could be attenuated in an analysis that includes roundtrip tickets.[43]

[43]We would like to thank an anonymous referee for raising this point.

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 and Zoom) provides additional opportunities to get in touch with new commercial partners who may eventually demand face-to-face meetings. 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 vital 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 A.1: Descriptive Statistics and brief description of the variables included in the analysis

Intertemporal pricing regressions: Equation (1) - Nbr. observations 43,160,581

Variables	Description	Mean	Std. Dev.	Min	Max
Price	One-way airline fare, in U.S. dollars	167.2	132.6	11.00	6,155
MktShare	Airline a's market share, computed using the number of daily nonstop flights on the route for sale on booking date b	0.289	0.262	0.000	1.000
HHI	Route Herfindahl-Hirschman Index on booking date b. In formula: $\sum_{a=1}^{n} \text{MktShare}_{ab}^2$	0.372	0.236	0.000	1.000
DaysToDeparture 1-2	Dummy=1 if DaysToDeparture $\in [1, 2]$	0.031	0.173	0.000	1.000
DaysToDeparture 3-6	Dummy=1 if DaysToDeparture $\in [3, 6]$	0.063	0.243	0.000	1.000
DaysToDeparture 7-13	Dummy=1 if DaysToDeparture $\in [7, 13]$	0.110	0.312	0.000	1.000
DaysToDeparture 14-20	Dummy=1 if DaysToDeparture $\in [14, 20]$	0.109	0.312	0.000	1.000
DaysToDeparture 21-60	Dummy=1 if DaysToDeparture $\in [21, 60]$, omitted category in the regressions	0.687	0.464	0.000	1.000
Covid	Dummy=1 if fare collection is after March 13$^{\text{th}}$, 2020	0.348	0.476	0.000	1.000
LCC	Dummy=1 if airline is a low-cost carrier (LCC)	0.192	0.394	0.000	1.000
Covid × LCC	Interaction of Covid variable with LCC variable	0.061	0.239	0.000	1.000
BookingMarch2020	Dummy=1 if the fare is collected in March 2020	0.101	0.301	0.000	1.000
BookingApril2020	Dummy=1 if the fare is collected in April 2020	0.072	0.259	0.000	1.000
BookingMay2020	Dummy=1 if the fare is collected in May 2020	0.071	0.257	0.000	1.000
BookingJune2020	Dummy=1 if the fare is collected in June 2020	0.073	0.260	0.000	1.000
BookingJuly2020	Dummy=1 if the fare is collected in July 2020	0.055	0.229	0.000	1.000
BookingAugust2020	Dummy=1 if the fare is collected in August 2020	0.017	0.131	0.000	1.000
InfectionsOrig	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
InfectionsDest	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
StayHomeOrig	Dummy=1 if a stay-at-home order is in effect in the origin airport state	0.142	0.349	0.000	1.000

StayHomeDest	Dummy=1 if a stay-at-home order is in effect in the destination airport state	0.132	0.339	0.000	1.000
Quarantine	Dummy=1 if a quarantine mandate is in effect in the destination airport state for travelers arriving from the origin airport state	0.065	0.246	0.000	1.000
Instruments					
5-week lag MktShare	Airline a's market share observed at t days to departure, computed using the number of daily nonstop flights on the route that depart 5 weeks before the examined flight at the same t days to departure	0.243	0.261	0.000	1.000
5-week lag HHI	Route Herfindahl-Hirschman Index observed at t days to departure, computed using the number of nonstop flights on the route that depart 5 weeks before the examined flight at the same t days to departure. In formula: $\sum_{a=1}^{n}$ 5-week lag MktShare_{at}^2	0.320	0.252	0.000	1.000

Price dispersion regressions: Equation (2) - Nbr. observations 788,114†

Variables		Mean	Std. Dev.	Min	Max
$\text{Gini}^{\text{lodd}}$	Flight-level Gini log-odds ratio of prices, $ln[Gini/(1-Gini)]$	-1.913	0.959	-8.638	1.267
$\text{Gini30}^{\text{lodd}}$	Flight-level Gini log-odds ratio of prices collected on the last 30 days to departure	-1.658	0.769	-8.536	1.289
$\text{Gini20}^{\text{lodd}}$	Flight-level Gini log-odds ratio of prices collected on the last 20 days to departure	-1.698	0.711	-8.661	1.348
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
$\text{P}_{\text{max}}-\text{P}_{\text{min}}$	Flight-level difference between the max and min price of the price distribution	199.2	205.0	1.000	4087
MktShare	Airline a's market share, computed using the number of daily nonstop flights on the route	0.317	0.281	0.000	1.000
HHI	Route Herfindahl-Hirschman index. In formula: $\sum_{a=1}^{n} \text{MktShare}_a^2$	0.382	0.346	0.001	1.000
Holiday	Dummy=1 if the flight departs during holiday	0.031	0.173	0.000	1.000
Weekend	Dummy=1 if the flight departs on a weekend	0.270	0.444	0.000	1.000
PartialCovidBook	Dummy=1 if the flight departs between March 13^{th}, 2020 and May 12^{th}, 2020	0.196	0.397	0.000	1.000
FullCovidBook	Dummy=1 if the flight departs after May 12^{th}, 2020	0.342	0.474	0.000	1.000
InfectionsOrigBook	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

InfectionsDestBook	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
StayHomeOrigBook	Fraction of days during the booking period that a stay-at-home order was in effect in the destination airport state	0.197	0.350	0.000	1.000
StayHomeDestBook	Fraction of days during the booking period that a stay-at-home order was in effect in the origin airport state	0.183	0.339	0.000	1.000
QuarantineBook	Fraction of days during the booking period that a quarantine mandate was in effect in the destination airport state for travelers arriving from the origin airport state	0.084	0.257	0.000	1.000
Instruments					
Past-year MktShare	Past-year value of MktShare	0.295	0.255	0.000	1.000
Past-year HHI	Past-year value of HHI	0.299	0.292	0.001	1.000
NbrCities	Number of U.S. cities (in units of 10) served nonstop by a given airline from the destination airport of a given route on the departure date	2.718	3.631	0.000	17.70

†Except for $\text{Gini30}^{\text{lodd}}$ and $\text{Gini20}^{\text{lodd}}$, which respectively encompass 569,272 and 499,726 observations.

Table A.2: First-stage estimates of *MtkShare* for Table 1

Dependent variable:	(1) MtkShare	(2) MtkShare	(3) MtkShare	(4) MtkShare	(5) MtkShare
5-week lag MktShare	0.059***	0.059***	0.059***	0.058***	0.058***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
5-week lag HHI	0.003	0.003	-0.000	0.004	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
DaysToDeparture 1-2	0.007***	0.006***	0.003***	0.002***	0.002***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
DaysToDeparture 3-6	0.006***	0.005***	0.002***	0.001***	0.001***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
DaysToDeparture 7-13	0.005***	0.004***	0.001***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DaysToDeparture 14-20	0.004***	0.004***	0.002***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Covid		0.011***		-0.002**	-0.005***
		(0.001)		(0.001)	(0.002)
Covid × LCCs					0.012***
					(0.003)
BookingMarch2020			0.000		
			(0.000)		
BookingApril2020			0.068***		
			(0.004)		
BookingMay2020			0.111***		
			(0.007)		
BookingJune2020			0.118***		
			(0.008)		
BookingJuly2020			0.123***		
			(0.009)		
BookingAugust2020			0.130***		
			(0.010)		
Covid × DaysToDep. 1-2				0.013***	0.013***
				(0.002)	(0.002)
Covid × DaysToDep. 3-6				0.013***	0.013***
				(0.002)	(0.002)
Covid × DaysToDep. 7-13				0.012***	0.012***
				(0.001)	(0.001)
Covid × DaysToDep. 14-20				0.012***	0.012***
				(0.001)	(0.001)
InfectionsOrig				0.002***	0.002***
				(0.001)	(0.001)
InfectionsDest				0.001**	0.001**
				(0.000)	(0.000)
StayHomeOrig				0.006***	0.006***
				(0.001)	(0.001)
StayHomeDest				0.011***	0.012***
				(0.002)	(0.002)
Quarantine				0.016***	0.016***
				(0.004)	(0.004)
R^2	0.654	0.570	0.048	0.419	0.415
Observations	42,801,983	42,801,983	42,801,983	42,801,983	42,801,983

Notes: 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. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table A.3: First-stage estimates of HHI for Table 1

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	HHI	HHI	HHI	HHI	HHI
5-week lag MktShare	-0.078***	-0.078***	-0.078***	-0.079***	-0.079***
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)
5-week lag HHI	0.165***	0.165***	0.164***	0.168***	0.168***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
DaysToDeparture 1-2	0.009***	0.007***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
DaysToDeparture 3-6	0.006***	0.005***	0.003***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
DaysToDeparture 7-13	0.004***	0.003***	0.001***	0.001***	0.001***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
DaysToDeparture 14-20	0.004***	0.003***	0.001***	0.001**	0.001**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Covid		0.014***		-0.001	-0.001
		(0.002)		(0.002)	(0.002)
Covid × LCCs					0.000
					(0.003)
BookingMarch2020			0.001		
			(0.001)		
BookingApril2020			0.080***		
			(0.006)		
BookingMay2020			0.104***		
			(0.009)		
BookingJune2020			0.107***		
			(0.009)		
BookingJuly2020			0.108***		
			(0.011)		
BookingAugust2020			0.110***		
			(0.012)		
Covid × DaysToDep. 1-2				0.008***	0.008***
				(0.003)	(0.003)
Covid × DaysToDep. 3-6				0.009***	0.009***
				(0.003)	(0.003)
Covid × DaysToDep. 7-13				0.007***	0.007***
				(0.002)	(0.002)
Covid × DaysToDep. 14-20				0.007***	0.007***
				(0.002)	(0.002)
InfectionsOrig				0.003***	0.003***
				(0.001)	(0.001)
InfectionsDest				0.002**	0.002**
				(0.001)	(0.001)
StayHomeOrig				0.008***	0.008***
				(0.003)	(0.003)
StayHomeDest				0.020***	0.020***
				(0.003)	(0.003)
Quarantine				0.015***	0.015***
				(0.006)	(0.006)
R^2	0.399	0.381	0.177	0.357	0.357
Observations	42,801,983	42,801,983	42,801,983	42,801,983	42,801,983

Notes: 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. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table A.4: Intertemporal pricing results with Ordinary Least Squares

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	ln(Price)	ln(Price)	ln(Price)	ln(Price)	ln(Price)
MktShare	-0.095***	0.016	-0.191***	0.055	0.067*
	(0.036)	(0.038)	(0.033)	(0.039)	(0.039)
HHI	0.052**	0.125***	0.040**	0.142***	0.138***
	(0.025)	(0.024)	(0.019)	(0.026)	(0.025)
DaysToDeparture 1-2	0.680***	0.755***	0.756***	0.806***	0.805***
	(0.019)	(0.019)	(0.019)	(0.023)	(0.023)
DaysToDeparture 3-6	0.444***	0.516***	0.516***	0.542***	0.542***
	(0.024)	(0.022)	(0.023)	(0.027)	(0.027)
DaysToDeparture 7-13	0.216***	0.275***	0.277***	0.274***	0.274***
	(0.020)	(0.018)	(0.019)	(0.020)	(0.020)
DaysToDeparture 14-20	0.021***	0.067***	0.068***	0.073***	0.073***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Covid		-0.837***		-0.793***	-0.730***
		(0.029)		(0.031)	(0.030)
Covid × LCCs					-0.288***
					(0.048)
BookingMarch2020			-0.607***		
			(0.018)		
BookingApril2020			-0.541***		
			(0.025)		
BookingMay2020			-0.352***		
			(0.018)		
BookingJune2020			-0.267***		
			(0.023)		
BookingJuly2020			-0.429***		
			(0.031)		
BookingAugust2020			-0.395***		
			(0.039)		
Covid × DaysToDep. 1-2				-0.146***	-0.147***
				(0.021)	(0.021)
Covid × DaysToDep. 3-6				-0.077***	-0.078***
				(0.024)	(0.024)
Covid × DaysToDep. 7-13				0.000	-0.000
				(0.015)	(0.015)
Covid × DaysToDep. 14-20				-0.019**	-0.020***
				(0.007)	(0.007)
InfectionsOrig				0.003	0.004
				(0.005)	(0.005)
InfectionsDest				-0.019***	-0.019***
				(0.004)	(0.004)
StayHomeOrig				-0.057***	-0.059***
				(0.017)	(0.017)
StayHomeDest				0.011	0.005
				(0.017)	(0.017)
Quarantine				-0.076***	-0.072***
				(0.025)	(0.025)
Adjusted R^2	0.171	0.300	0.261	0.304	0.307
Observations	43,160,581	43,160,581	43,160,581	43,160,581	43,160,581

Notes: 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. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table A.5: Placebo test on intertemporal pricing results

	(1)	(2)	(3)	(4)
Dependent variable:	ln(Price)	ln(Price)	ln(Price)	ln(Price)
MktShare	-0.032	-0.250	-0.009	-0.226
	(0.258)	(0.252)	(0.259)	(0.253)
HHI	0.242***	0.122	0.238***	0.120
	(0.082)	(0.077)	(0.082)	(0.077)
DaysToDeparture 1-2	0.744***	0.753***	0.722***	0.731***
	(0.019)	(0.019)	(0.019)	(0.019)
DaysToDeparture 3-6	0.506***	0.514***	0.485***	0.494***
	(0.023)	(0.023)	(0.022)	(0.023)
DaysToDeparture 7-13	0.268***	0.275***	0.251***	0.258***
	(0.019)	(0.019)	(0.018)	(0.018)
DaysToDeparture 14-20	0.061***	0.067***	0.048***	0.055***
	(0.007)	(0.007)	(0.007)	(0.007)
BookingJanuary2020			0.121***	0.117***
			(0.005)	(0.005)
BookingFebruary2020	0.057***	0.048***	0.176***	0.163***
	(0.005)	(0.005)	(0.009)	(0.009)
BookingMarch2020	-0.554***	-0.521***	-0.425***	-0.396***
	(0.020)	(0.019)	(0.022)	(0.022)
BookingApril2020	-0.512***	-0.192***	-0.380***	-0.066***
	(0.031)	(0.025)	(0.032)	(0.026)
BookingMay2020	-0.333***	-0.101***	-0.196***	0.031
	(0.035)	(0.033)	(0.035)	(0.033)
BookingJune2020	-0.246***	-0.172***	-0.101**	-0.033
	(0.040)	(0.039)	(0.040)	(0.039)
BookingJuly2020	-0.406***	-0.248***	-0.252***	-0.103**
	(0.045)	(0.042)	(0.045)	(0.043)
BookingAugust2020	-0.368***	-0.245***	-0.200***	-0.086*
	(0.051)	(0.047)	(0.051)	(0.047)
InfectionsOrig		-0.006		-0.006
		(0.006)		(0.006)
InfectionsDest		-0.024***		-0.023***
		(0.005)		(0.005)
StayHomeOrig		-0.219***		-0.219***
		(0.022)		(0.022)
StayHomeDest		-0.147***		-0.147***
		(0.023)		(0.023)
Quarantine		-0.108***		-0.108***
		(0.028)		(0.028)
Kleibergen-Paap χ^2 Stat.	37.258***	37.585***	37.254***	37.580***
Kleibergen-Paap Wald F Stat.	33.488***	33.948***	33.477***	33.938***
Adjusted R^2	0.228	0.250	0.231	0.253
Observations	42,801,983	42,801,983	42,801,983	42,801,983

Notes: $MktShr$ and HHI are treated as endogenous variables and instrumented for using five-week lags of $MktShr$ and HHI on the same route and number of days to departure as the observed flight. 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. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table A.6: First-stage estimates for Table 2

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	MktShare	HHI	MktShare	HHI	MktShare	HHI
Past-year MktShare	0.497***	-0.307***	0.396***	-0.129***	0.346***	-0.054
	(0.034)	(0.053)	(0.025)	(0.047)	(0.022)	(0.042)
Past-year HHI	-0.007***	0.018*	-0.003*	0.021**	-0.002	0.019**
	(0.002)	(0.009)	(0.001)	(0.009)	(0.001)	(0.008)
NbrDestinations	-0.004*	-0.042***	0.000	-0.034***	0.002	-0.028***
	(0.002)	(0.007)	(0.002)	(0.006)	(0.002)	(0.006)
Holiday	0.004***	-0.011**	0.006***	-0.007	0.006***	-0.006
	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)
Weekend	0.001	-0.002	0.002**	-0.001	0.002***	-0.001
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
PartialCovidBook	0.026***	0.047***	0.018***	0.026***	0.013***	0.017**
	(0.006)	(0.011)	(0.005)	(0.008)	(0.004)	(0.007)
FullCovidBook	0.009	-0.011	0.016***	-0.012	0.017***	-0.011
	(0.006)	(0.011)	(0.006)	(0.012)	(0.005)	(0.012)
InfectionsOrigBook	0.003	0.009*	0.004	0.010**	0.003	0.010**
	(0.002)	(0.005)	(0.003)	(0.004)	(0.002)	(0.004)
InfectionsDestBook	0.004***	0.008**	0.005**	0.010**	0.004*	0.008**
	(0.001)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)
StayHomeOrigBook	0.027***	0.043***	0.074***	0.126***	0.084***	0.115***
	(0.007)	(0.012)	(0.012)	(0.027)	(0.011)	(0.026)
StayHomeDestBook	0.016**	0.039***	0.053***	0.039	0.053***	0.050**
	(0.008)	(0.014)	(0.012)	(0.026)	(0.012)	(0.024)
QuarantineBook	0.013	0.005	0.005	-0.003	-0.001	-0.028
	(0.015)	(0.022)	(0.018)	(0.030)	(0.015)	(0.026)
R^2	0.078	0.038	0.076	0.025	0.069	0.016
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 $\ln(\text{P}_{\text{max}}-\text{P}_{\text{min}})$ 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, 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.