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Strategic Responses Under Increasing Uncertainty: Flight Cancellation Decisions by Domestic Airlines

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Abstract

In this study, we assess the influence of strategic interaction on airlines' decisions to cancel flights amid the heightened uncertainty of the early Covid-19 pandemic in Japanese domestic market. Airlines were compelled to modify their operations, predominantly through the cancellation of scheduled flights. Leveraging a novel dataset comprising airlines' public announcement, we examine the timing and magnitude of flight cancellation by integrating with data on the progression of the pandemic and the enactment of public policies. Our analysis of cancellation practices of airlines indicates that the risk of infections significantly influenced airline cancellations; specifically, an increase in the infection risk by 30% is correlated with a 10% rise in the cancellation rate during the early period of the pandemic. Additionally, our results reveal that strategic interaction also relates to the dynamics of flight cancellation decisions. The hazard rate of cancellation event is more than 30% lower in duopoly market, while it gets closer to that of monopoly market as the departure date approaches, which is in line with the implication of the war of attrition.

Keywords: War of attrition; Market Structure; Uncertainty; Duration; Announcement

JEL classification: C43; D43; L13; L93

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1 Introduction

The outbreak of COVID-19 in late 2019 swiftly escalated into a global pandemic, creating an unprecedented crisis with wide reaching effects across multiple sectors. Among the hardest hit was the aviation industry, which faced an abrupt and steep decline in passenger numbers due to travel restrictions, lockdowns, and a significant shift in public sentiment regarding travel safety around the world. The pandemic disrupted the balance of supply and demand in a market characterized by high passenger volumes and frequent flights

Flight cancellations, usually considered a measure of last resort in airline operations, rapidly became a strategic tool for managing the economic fallout of the pandemic. These cancellations were not merely reactions to decreased passenger demand. They were also indicative of a wider array of strategic considerations, encompassing the uncertainty surrounding infectious risks, the evolving landscape of policy responses, and the dynamics of competitive interactions within the industry. Using pandemic's uncertainty as an quasi-experiment, this paper examines how increasing uncertainty during the COVID-19 alters the strategic responses of airlines particularly regarding flight cancellation decisions in varying market structures.

This study conducts an analysis using unique data on the timing of flight cancellation announcements collected by the authors. Airlines sometimes cancel flights on the day of departure, but can also announce cancellations up to three months in advance. Announcing cancellations early has the benefit of reducing the burden on passengers scheduled to fly. Conversely, delaying cancellation announcement until the day of flight allows airlines to retain the option of operating the flight.

Given the Japanese domestic air market's structure, predominantly dominated by either or both of the major carriers, this paper aims to quantitatively reveal how the timing of these announcements varies with market structures and how these timings change in response to the increasing uncertainty brought about by the COVID-19 pandemic.

Our reduced-form analysis of announced cancellation rate shows that the timing of cancellation announcements is significantly affected by both COVID-19 infection risks and market structure. We also use IV estimation to deal with the endogeneity of the infection risks. Our estimates suggest that an increase of 30% in the infection risk from median value would increase the cancellation rate by 10% in April, early stages of the pandemic. The effect of infection risks shrinks over time: in August, the same increase in infection risk would increase the cancellation rate by 0.4%.

To further explore the dynamics of cancellation behavior in relation to strategic incentives, we conduct a duration analysis of the timing of cancellation announcements. We find that the timing of announcements is significantly affected by the market structure: the hazard rate of announcement is 30% lower in duopoly markets than in monopoly markets. Our result of Cox proportional hazard model also suggests that the hazard rate significantly differs over time: it is the lowest around 2 weeks prior to the departure date, and gradually increases as the departure date approaches. Such a result is consistent with the implication of strategic delay, where competing airlines engage in war of attrition to retain the option of operating the flight.

Our paper contributes to two strands of literature. First is the literature of airlines' operational decisions. As well as many studies on flight delay, or on-time performance of airline operation, several papers study the determinants of flight cancellations (Fukui and Nagata 2014; Rupp and Holmes 2006). Alderighi and Gaggero (2018) focuses on airline alliance and shows that the alliance membership increases the likelihood of flight cancellation. Our study, while interested in the flight cancellation and its relation to strategic incentives, put more emphasis on the dynamics of cancellation decisions. To gain insights, we borrow the framework of war of attrition, such as Fudenberg and Tirole (1986) and Hendricks and Porter (1996).

The second strand of literature our study contributes to is the literature on the effect of COVID-19 on industry and economy both in Japan and other countries. Researchers study the devastating effect of COVID-19 and a series of policy measures aiming to contain the infection or help economies recover (Ando et al. 2020; Fukuda 2023, for Japanese economy). Kawaguchi, Kodama, and Tanaka (2021) study the quasi-lock down measure taken in Japan during the early stage of the pandemic and lump-sum subsidies to small businesses. By using survey data of business owners' expectation, they show the significant influence of both business suspension measures and subsidies, which is also affected by the managers expectation of the future. We also study the effect of COVID-19 in the context of Japanese domestic air market, and provide insights on how strategic incentives play a role even in the midst of the pandemic.

The reminder of this paper is organized as follows. In Section 2, we provide a background of our study and describe how Japanese domestic airlines respond to the pandemic. We present statistical evidence that flight cancellation, not ticket prices, seemed to be a primary instrument to respond to the pandemic. Section 3 discusses data that used in this study. Sections 4 and 5 show estimation results. Section 4 explains the variation of flight cancellation rates, indexed by date of cancellation announcement and by date of flight. Section 5 performs duration analysis to explain how the timing of cancellation announcement differs by market structures.

2 Background and Data of this study

The COVID-19 pandemic profoundly disrupted air travel worldwide, a phenomenon that was not limited to international routes but also deeply affected domestic flights within Japan, the primary focus of our study. From March 1st to December 1st of 2021, a period critical in the pandemic's timeline, Japan experienced significant fluctuations in COVID-19 infection rates. These variations, characterized by sharp increases and unpredictable peaks and troughs of the cases numbers shown in Figure 1, mirror the global unpredictability of the virus's spread.

Alongside reported COVID-19 cases, the figure also depicts the daily count of cancellation rates of Japan's domestic flights. It illustrates a pattern of fluctuation with intermittent peaks that suggest sporadic responses to changing circumstances. At first glance, the two datasets shown in Figure 1 do not appear to be closely correlated; the frequency and magnitude of flight cancellations do not seem to directly mirror the ebb and flow of COVID-19 case numbers. This figure sets the stage for our investigation into the complexities of the airline industry's cancellation choices during the COVID-19 pandemic, foreshadowing a deeper exploration into how airlines navigate operational challenges under uncertainty in public health crises.

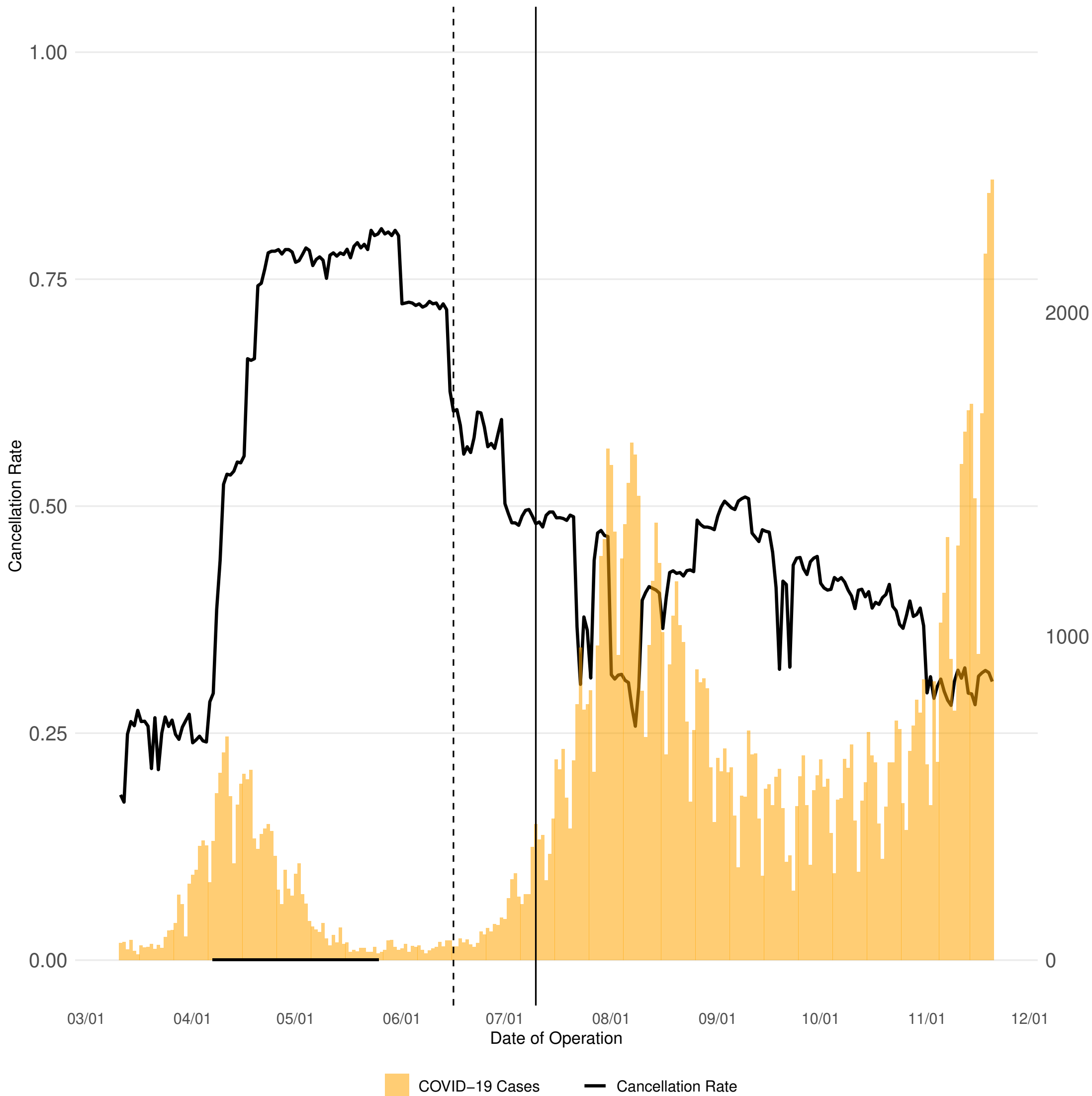
2.1 Flight cancellation as a predominant response to COVID-19

First, we argue that in response to the COVID-19 pandemic and the resulting demand shock, airlines in Japan primarily opted for flight cancellations. Figure 1 illustrates this trend by displaying the cancellation rates of Japanese domestic airlines with the timeline of COVID-19 case surges in Japan. The cancellation rates, calculated as the ratio of canceled to scheduled flights, spiked to 75% in March 2020 and stayed above 50% until June, coinciding with the pandemic's first peak. These rates persisted at levels above 25% for the rest of 2020, which includes the second wave of infections in August and the third in late November. Note that in post-COVID periods, we observe sub-5% cancellration rate[1] in contrast to this period. This pattern of high cancellation rates will be further analyzed later in this section.

Compared to the cancellation rates, the price changes are much less pronounced. To check the price changes, we collect the fares of flights posted on the airlines' website for 1, 3, 7, and 28 days

1. We collect cancellation records of the two airlines studied in this paper in post-COVID period of May to November 2023. During this period, both airlines did not issue any preannouncement caused by COVID-19 infection. Cancellation records, both during COVID and post-COVID, were retrieved from airlines webpages issuing certificate on delay/cancellation of a flight.

Figure 1: Cancelled flights and the evolution of COVID-19



Note: In both panels, the orange bars depict newly confirmed cases of COVID-19 infections in Japan, and the line shows the cancellation rates in Japanese domestic airlines. The solid horizontal line lying from April to May 2020 represents the period of the state of emergency, and the two vertical lines represent the dates when the Goto Travel Campaign was announced and deployed, respectively. The detail of those policies are discussed in Section 3.

Table 1: T-test for posted prices of canceled and not canceled flights

	Canceled	Not Canceled	Difference
Canceled from 28 days to 7 days	38.22	38.43	−0.21
			(1.43)
Canceled from 7 days to 3 days	38.46	38.52	−0.06
			(4.09)
Canceled from 3 days to 1 days	38.51	38.40	0.11
			(5.52)

Note: This table shows the results of t-tests for posted prices. The first two columns show the prices of each group, canceled flights and not canceled, in thousand Japanese Yen. The null hypothesis is that the mean of posted fares of the canceled flights are different from the mean of not canceled. Each row represents the timing of the flight cancellation. Standard errors are in the parenthesis. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

prior to the departure date during the period of May 2020 to November 2020. We conduct two types of analysis. First, we examine the correlation between posted prices and COVID-19 infection. If airlines adjust the prices to demand shock caused by the COVID-19 infection, there is likely to be some evidence of correlation. However, Table A.1 shows no significance when we regress the posted prices on the infection measure and relevant policy variables. This is in contrast with the results using cancellation rates in the next section. The present results suggest that the airlines' responses to COVID-19 are not through price changes.

To further check whether the airlines are adjusting prices, we compare the posted prices of the canceled flights with those of the non-canceled flights. Given that canceling a scheduled flights is costly for airlines, if the airlines are adjusting prices, we expect the posted prices of the canceled flights to be lower so that the airlines can attract more passengers on those flights and avoid cancellation. Table 1 shows the results of the t-test comparing the posted prices of the canceled flights with those of the non-canceled flights. The table shows that the posted prices of the canceled flights are not significantly different from those of the non-canceled flights. Those results suggest that prices are not the primary device for airlines to respond to COVID-19.

2.2 Preannounced cancellations

Throughout the rest of this paper, our analysis primarily centers on the preannouncement of flight cancellations. Notably, over 90% of cancellations in our dataset were preannounced before the departure date (refer to Table A.2), indicating a distinct pattern during the COVID-19 period. This focus on preannouncements provides clearer insights into airlines decision-making processes and their response to the pandemic.

One concern of using preannouncement data is potential bias: the flights that are preannounced to be canceled may be different from those that are not. To address this concern, we examine the frequency of preannounced cancellations over time and by origin-destination (OD) pair. Figure 2 shows the proportion of flights of which cancellation was not announced . The dashed vertical lines represent the dates when typhoons hit the south-west parts of Japan, which are likely to be unanticipated. The rate of sudden cancellations (those not preannounced) remained consistently below 5%, except during typhoons. Given that the COVID-19 infection fluctuates over time, the persistently low rate of sudden cancellations suggests that the preannounced cancellations are not affected in a singificant way.

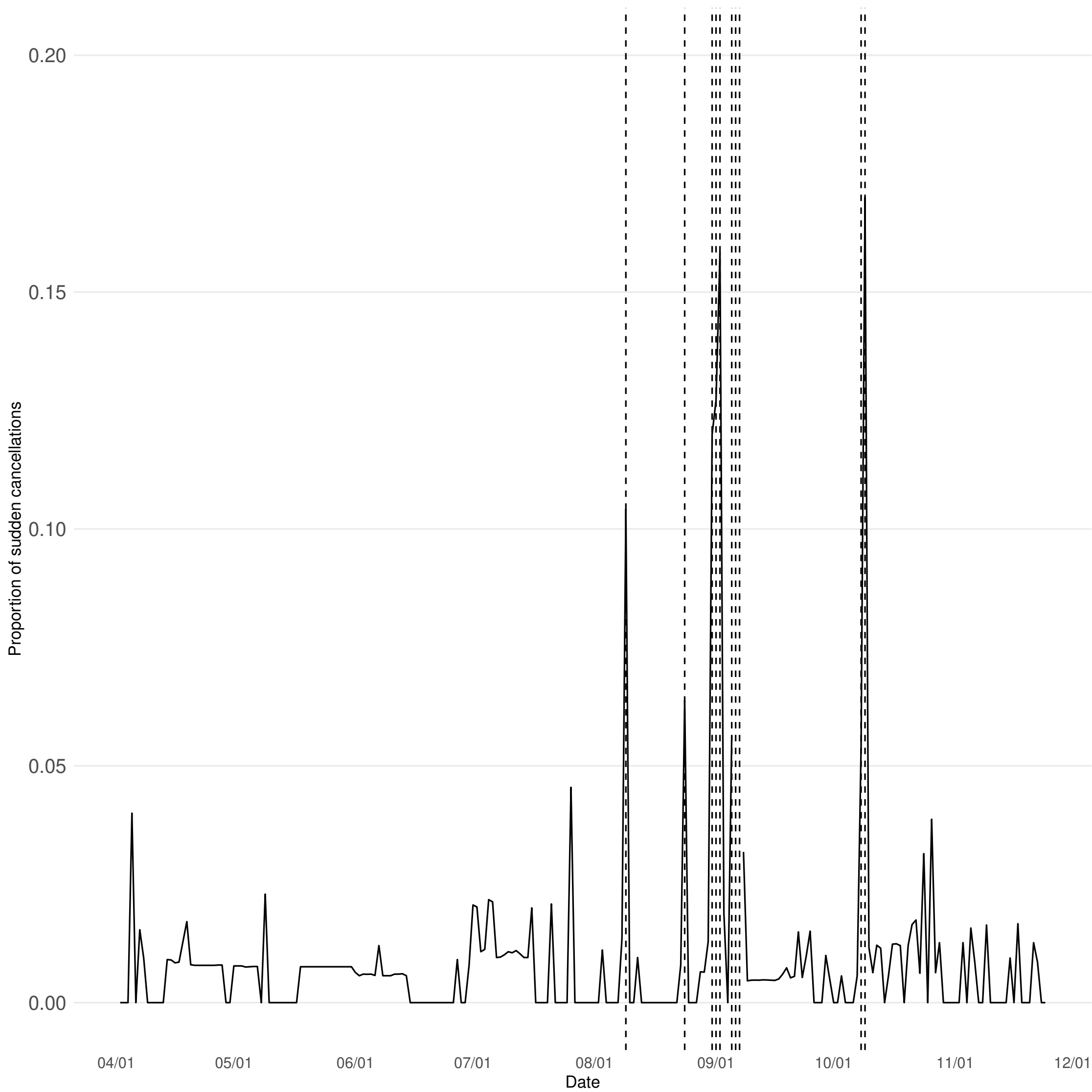
Next, we assessed the OD-based bias in preannouncements. By considering the number of scheduled flights and market size for each OD, we examined if these factors influenced the likelihood of preannouncements. we examine the proportion of preannounced cancellations by OD. Specifically, we take the number of scheduled flights and market size by OD to examine if these factors influenced the likelihood of preannouncements. We run a regression of whether a canceled flight is preannounced. Table 2 shows the results. The first two columns use the number of scheduled flights as the OD characteristics and the last two columns use the market size. Regardless of the specification of fixed effects (OD-level or departure and arrival airport level), those OD characteristics does not show singificant correlation with the occurance of sudden cancellations. Thus, we conclude that preannounced cancellations are not significantly biased in terms of OD characteristics.

Table 2: Results of preannouncement regressions

	(1)	(2)	(3)	(4)
No. flights	0.001	0.000		
	(0.005)	(0.001)		
Market Size			0.498	−0.010
			(42.24)	(0.892)
Observations	31,685	31,685	31,685	31,685
FE: Date	Yes	Yes	Yes	Yes
FE: OD	Yes		Yes	
FE: Departure airport		Yes		Yes
FE: Arrival airport		Yes		Yes

Note: This table shows the results of regression. Standard errors in the parenthesis are clustered in ODs and dates. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Figure 2: Aggregate proportion of preannounced cancellations



Note: The solid line shows the proportion of flights of which cancellation was not announced (*sudden cancellation*). The dashed vertical lines represent the dates when typhoons hit the Kyushu region, south-west parts of Japan.

3 Data and Descriptive Evidence

In this section, we provide a formal description of our data set of preannounced cancellations, which is characterized by the announcement date and the cancellation date for each flight. This enables us to look into two aspects of the cancellation behavior: quantity and duration. Our descriptve evidence suggests that both measures are affected by demand shocks including COVID-19, policy changes, and market structure.

We construct the preannouncement data set of two major Japanese airlines, ANA and JAL, containing a comprehensive history of their announcements as to domestic flights from March 1st to November 30th in 2020. We retrieve those announcement records from airlines' press releases[2]. Each announcement contains the date and the number of canceled flights for each route.

One caveat of our dataset is that the two airlines are not the only ones competing in the Japanese domestic market during the period. However, we believe that the following analysis still provides insights into the airlines behavior and their strategic incentive. One primary reason is that the present two are the distinct and predominant player in the market in terms of prices and market share. In 2021, ANA and JAL earned 1,020 and 683 billion yens in revenue, respectively, which is more than 10 times larger than the third largest airlines.

Table 3 shows the summary statistics of our cancellation data. We split our sample into three groups by market size. The number of scheduled flights are significantly different across market size. The market structure also varies, and the monopoly routes are concenrated in medium-sized markets. To capture the degree of infection at each region, we define the infection risk as the number of confirmed cases per 100,000 population of each prefecture the aiport is located in (Kawaguchi, Kodama, and Tanaka 2021). We observe that the infection risk is higher in large markets, which is reasonable given that these prefectures tend to have urban areas with high population density. Contrary, the cancellation rate does not show a clear distinction between market size.

3.1 Description of cancellation behavior

Table 3 also shows the summary statistics of the duration of cancellations, which is another aspect of cancellation behavior. We define the duration of a canceled flight as the number of days from the preannouncement date to the departure date. In theory, airlines could cancel flights at the very

2. For example, ANA reports the cancellation decisions on its webpage entitled by *Temporarily Change Service on Domestic Routes Due to the Coronavirus.*

Table 3: Summary statistics of flight and cancellation characteristics

Market Size	Below Median	Above Median
Flight characteristics		
Number of scheduled flights	9.18	13.74
	(1.17)	(2.14)
Monopoly Routes (%)	16.2	7.0
Covid variables		
Infection risk (dep) at τ	0.50	0.62
(preannouncement date)	(0.81)	(0.78)
Infection risk (arr) at τ	0.50	0.61
	(0.80)	(0.78)
Infection risk (dep) at t	0.63	0.83
(departure date)	(0.94)	(0.99)
Infection risk (arr) at t	0.62	0.82
	(0.93)	(0.97)
Cancellation characteristics		
Cancellation rate	0.26	0.21
	(0.14)	(0.15)
Duration $t - \tau$	23.96	24.01
	(12.59)	(12.93)

Note: This table shows the summary statistics of our preannouncement/cancellation data. We split our sample into two groups by market size, depending on whether they are above the median or below. τ and t refers to the timing of observation: τ is preannouncement date and t departure date of each flight. Standard deviations are in the parentheses.

last minute of departure date, as observed in conventional studies of flight cancellation (Rupp and Holmes 2006). As shown in Table 3, the average duration of cancellations is 24 days with a large standard deviation of 13 days. Those numbers suggest that airlines are canceling flights in advance, adjusting their timing of cancellation decisions.

To further understand the duration and cancellation behavior, we show how the duration varies over time in Figure 3. As airlines announce the cancellations of multiple departure dates at once, we show the durations of each preannouncement as line between shortest and longest durations, i.e., duration of nearest and furthest departure dates. The duration tend to be smaller (both for the nearest and furthest departure dates) during the first peak of the pandemic (March to May), and gets longer after that period, especially during off-peak time. This suggests that the airlines are adjusting the timing of cancellation decisions in response to the demand shocks over time.

There also exist two policy changes that might affect the airlines' behavior during these periods. Figure 1 shows (i) rise in flight cancellations during the first policy period, Emergency declaration from late April to the end of May, and (ii) decline in the cancellation rate as the second policy, Goto Campaign, is implemented.

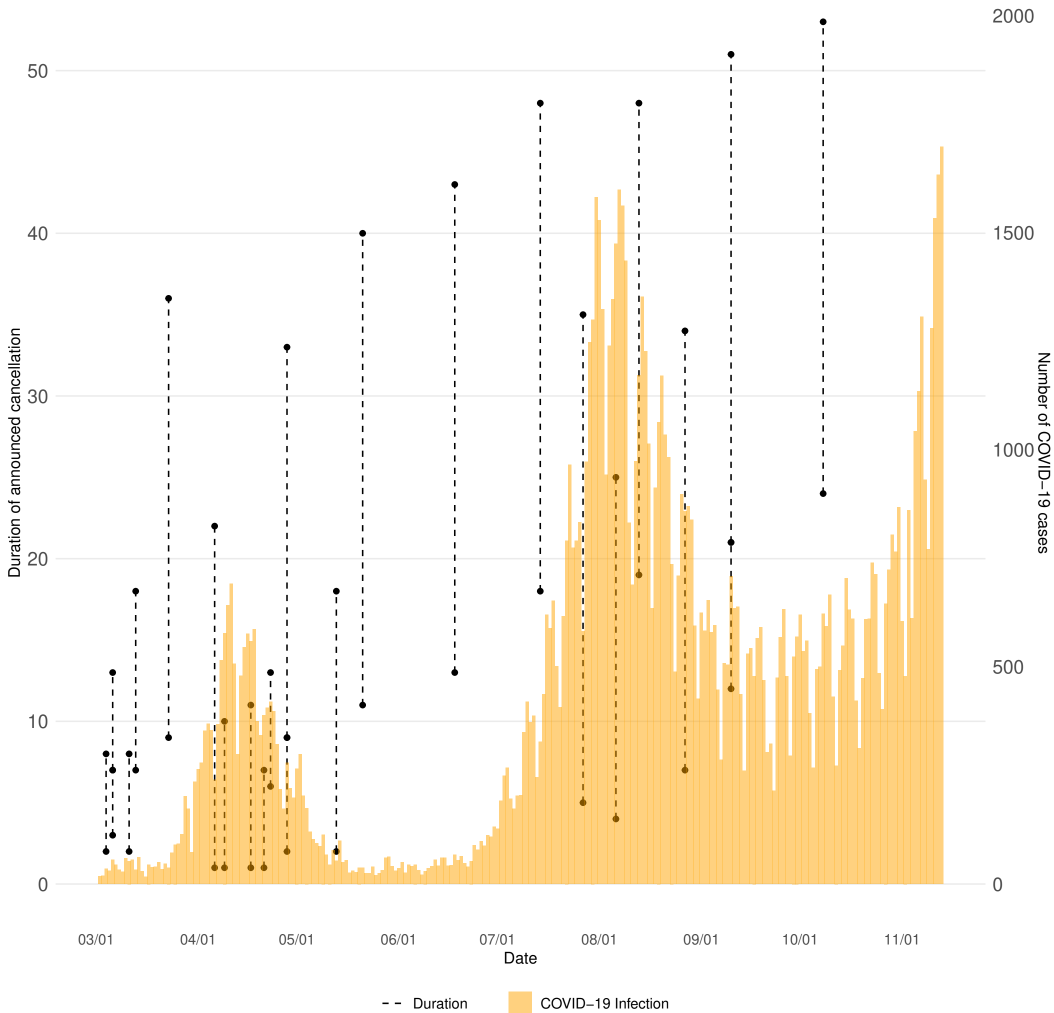
The first relevant policy is the declaration of emergency state from April to May, which aimed to contain the infection by making a request for businesses and citizens to refrain from social activities. As Kawaguchi, Kodama, and Tanaka (2021) point out, although it was a relatively mild restriction without law enforcement, the declaration and business-suspension request had a significant impact on Japanese business sales. The deployment of emergency declaration unfolded in four parts.

On April 7, the Japenese government declared the state of emergency until May 6 in 7 prefectures (Tokyo, Kanagawa, Saitama, Chiba, Osaka, Hyogo, and Fukuoka). Next, on April 16, the government expanded coverage of the emergency declaration to all prefectures in Japan. As a third phase, on May 4, the expected duration of emergency declaration is extended to May 31. Finally, on May 14, the government lifted the declaration in 39 among 47 prefectures while the remaining 8 prefectures were still in emergency state. The declaration on the remaining prefectures got removed on May 25[3]. As a result of this anti-contagion policy, the number of infection reduced significantly: in Tokyo, the number of confirmed cases is as small as 8 out of 9.2 million population.

The geographic variation in this policy implementation allows us to conduct a simple pre-post change analysis to explore the effect of the policy on the cancellation behavior. We split our

3. More specifically, on May 21, the emergency declaration was lifted on 3 prefectures out of 8. Then, on May 25, the declaration was removed in all prefectures. Since no announcement was made from May 21 to May 25, we consider these two periods of partial lifting as a whole.

Figure 3: Duration and COVID-19 infection

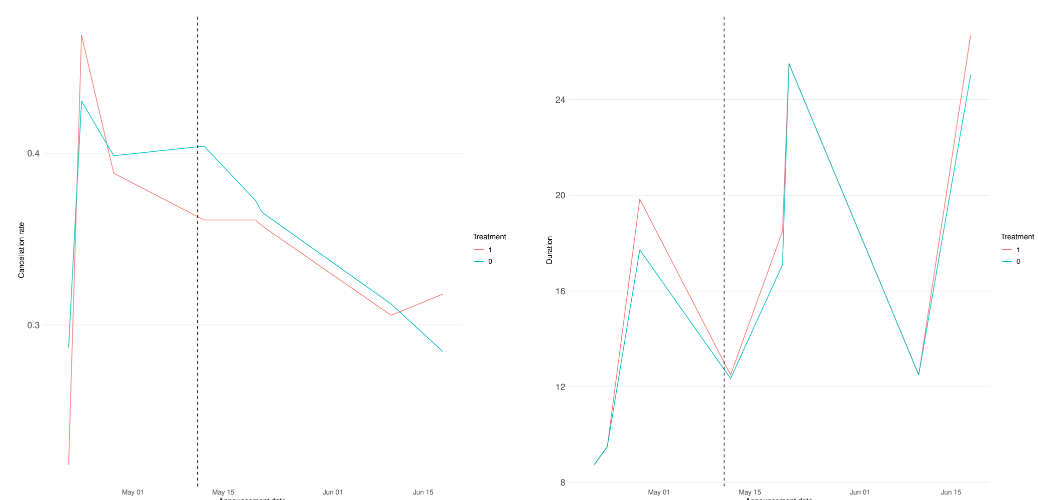


Note: This figure shows the duration of cancellation of ANA for each preannouncement. Duration is defined as the difference between preannouncement date and departure date in days. The two dots depict the shortest and largest durations for each preannouncement. The orange bars represent the newly confirmed cases of COVID-19 infections in Japan.

sample into two groups: the treatment group consists of the flights that are out of the scope of the emergency declaration after May 14 (with OD in the seven prefectures under restriction), and the control group consists of the flights that are still in the scope of the emergency declaration[4]. We take the announcement right before the policy change on May 14 as the pre-period and the announcement next to the policy change as the post-period. Figure 4 shows the results of pre-post change of the cancellation rate and duration.

We see that the cancellation rate of the treated group which was lifted from the emergency declaration is lower than that of the control group by around 3% with a change in the direction of the change. This, although not statistically supported, suggests that the policy change might have affected the cancellation rate. On the other hand, the duration of cancellations do not show a distinct pattern as the cancellation rate does. The decision-making process might be affected by the policy change, but the way airlines respond to the policy can be different between the variables they control.

Figure 4: Policy change and cancellation behavior



(a) Cancellation rate

(b) Duration

Given the success in the anti-contagion policy and damages of travel and hotel industries, the Japanese government implemented a stimulus package named ‘Goto travel’, which is the other relevant policy in our study. The policy tried to stimulate the travel demand by reimbursing the travllers with up to half of their travel expense[5]. The implementation of this policy is announced

4. Given that the control group consists of flights in relatively small market, we exclude the flights in large markets from the analysis.

5. The reimbursement is limited to 20,000 JPY (about $200) for over-night trip and 10,000 JPY ($100) for one-day trip.

on June 16 by the Ministry of Land, Transport, Infrastructure, Transport and Tourism with an expectation that the policy starts at the beginning of August 2020. On July 10, MLTI announced that the policy starts on July 22 for six months.

For the later analysis, we split the period into two: one is from June 16 to July 22, when firms know the incoming demand-stimulating policy, and the other is after July 22 to the end of our sampling period, when the policy is in effect.

The exact definition of the dummy variables of Emergency declaration and Goto campaign is shown in Table A.3.

3.2 Strategic interaction

Finally, we provide a descriptive evidence of the market structure affecting the airlines' cancellation behavior. Figre 5 shows the difference in cancellation rate and hazard risk between monopoly and duopoly routes[6]. The figure shows that the cancellation rate is higher in monopoly routes over time, while the overall trends are the same. This is consistent with the general idea of Cournot competition: the market output in oligopoly market is larger than in monopoly.

For duration, the right panel of Figure 5 shows distribution of the cancellation rates in terms of the duration. It shows that while monopoly routes tend to have constant rate for durations longer than 20 days, duopoly routes have a declining pattern. This, combined with the consistently lower cancellation rate in duopoly routes, suggests that airlines in duopoly routes are more likely to cancel flights close to the departure date.

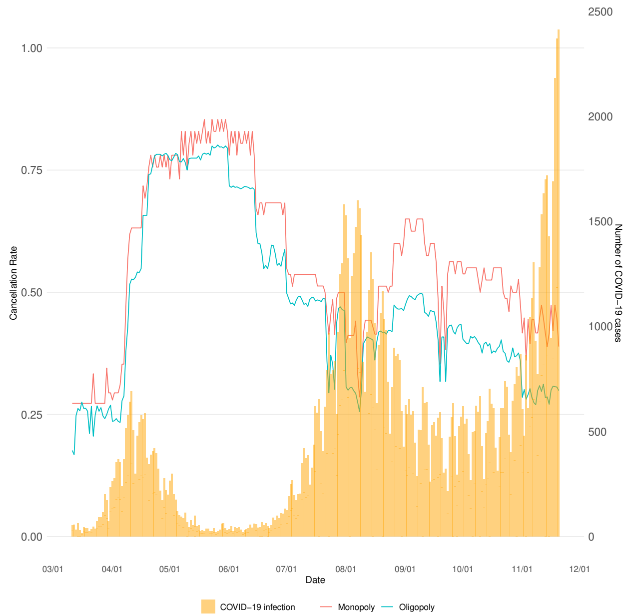
One concern against these finding of strategic interaction is that the monopoly routes are concentrated in small markets, where the number of scheduled flights are lower and infection risk is samller. Some might argue that the airlines behavior is driven by the market-level characteristics, including the different situation of COVID-19 infection, rather than the market structure. In the next section, we will address this concern by conducting a regression analysis.

4 Empirical analysis of airline behavior during the pandemic

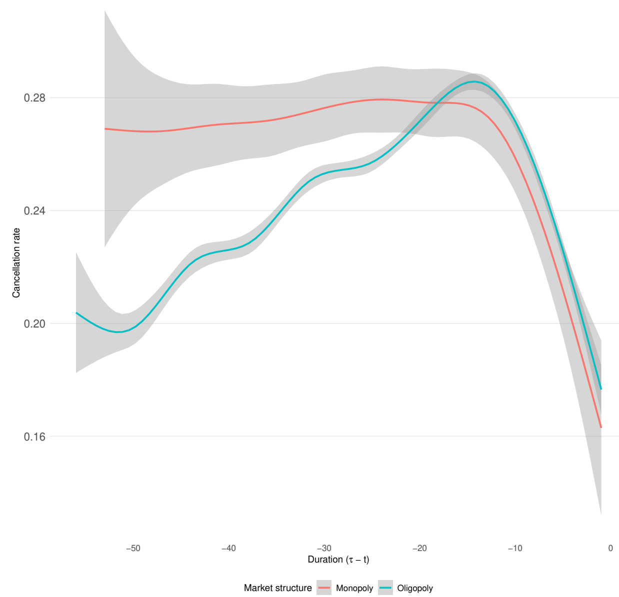
To examine the relationship between cancellation behavior and COVID-19 with related policies, we conduct panel regression. We find that the risk measures of COVID-19 infection are strongly associated with cancellation rates; anti-contagion policies have a strong impact on cancellations

6. We define duopoly routes as the routes that are operated by both airlines in our dataset. Since we do not observe the other airlines, the definition of market structure might be different as we expand to the entire industry.

Figure 5: Cancellation behavior and market structure



(a) Cancellation ratio



(b) Duration and cancellation ratio

Note: The left panel shows the time-series evolution of cancellation rate in monopoly and duopoly routes with COVID-19 infection cases. The right panel shows the nonparametric distribution of cancellation rate in terms of duration.

when an additional extension is decided; strategic interaction does affect the short- and medium-term cancellation behavior.

4.1 Model of dynamic cancellation decision

The previous section has provided descriptive evidence suggesting (i) airlines are likely to optimize both cancellation rate and duration given the COVID-19 infection situation and policy environments, and (ii) strategic incentives may play a role in their decision-making process. To understand the mechanism behind those observations, first we develop a theoretical model of a monopoly airline's dynamic decision problem of flight cancellations. We then discuss the possible extension of the model to duopoly markets. Our approach is facilliated by the literature of firms' entry/exit such as Mazzeo (2002) and Seim (2006) and that of war of attrition (Fudenberg and Tirole 1986; Hendricks and Porter 1996; Takahashi 2015).

Consider a monopoly airline in a given market deciding when to cancel how many flights, i.e., she decides the announcement date $\tau \in [0, t]$ and volume of canceled flights $f \in [0, 1]$. The airline's ex-post profit function is given by $\pi(f, \varepsilon_t)$ where ε_t is the demand shock realizing at the dapartur date t. To fit our dataset, we assume that π is decreasing in ε_t. This is best understood when we view ε_t as the infection risk of COVID-19 realizing at t. The higher the infection risk, the lower the demand for air travel.

On each possible announcement date τ, the airline receives a signal η_τ about the demand shock (or the infection risk on date τ). The two random values are assumed to follow bivariate normal distribution:

$$\begin{pmatrix} \varepsilon_t \\ \eta_\tau \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} \mu_\varepsilon \\ \mu_\eta \end{pmatrix}, \begin{pmatrix} 1 & \rho\sigma(\tau) \\ \rho\sigma(\tau) & \sigma^2(\tau) \end{pmatrix}\right) \tag{1}$$

where ρ captures how informative the signal η is about the demand shock ε, and $\sigma(\tau)$ measures the accuracy. We assume $\sigma' < 0$, i.e., as the airline waits and collects more information, the accuracy of the signal increases.

The airline knows the information structure except for the realization of ε_t. The airline's problem is to choose the optimal announcement date τ and the volume of canceled flights f to maximize the expected profit:

$$\max_\tau \quad \Pi(\tau) - C(\tau)$$
$$\text{where} \;\; \Pi(\tau) = \max_f \; \mathbb{E}_{\varepsilon_t}\left[\pi(f, \varepsilon_t)|\eta_\tau\right]$$

where C is time-dependent cost, representing the cost of delay[7].

We present some key implications of our model in the following propositions. The detail is provided in Appendix B.

Proposition 1. *The announced cancellation rate, $1 - f^*$, is increasing in the infection risk on the announcement date, η_τ.*

The first proposition states that the optimal cancellation rate is increasing in the severity of infection, such as observation of high infection risk. This result comes from the informativeness of today's signal η_τ about the infection in the future ε_t. If the airline observe a bad signal of spreading disease, she expects the future infection to be severe as well, thus leading to more cancellations.

7. In our setting, airlines are obliged to redeem the ticket price when they cancel the flight, which airlines incur more as they delay their decisions and have more passengers purchase the tickets.

Proposition 2. *Under a certain parametric condition, the optimal announcement date τ^* is decreasing in the uncertainty of the signal, $\sigma(\tau)$. That is, the airline is more likely to announce the cancellation earlier when the signal is more uncertain.*

The intution of this proposition is as follows. The airline's announcement timing is determined by the trade-off between the marginal cost of delay represented by $C(\tau)$ and the marginal benefit of collecting more information. The latter comes from the *good news* that the infection situation might be better on the departure date. When the uncertainty of the signal gets higher, this marginal benefit of confirming the good news decreases. Hence, the airline has less incentive to wait and announce the cancellation earlier.

The second proposition indicates that controlling the uncertainty of the infection spread is crucial to understand the airlines' decision-making process. We try to implement this idea in our empirical analysis by using various controls such as announcement date fixed effects, departure and arrival airport fixed effects, and inclusion of infection risk variables.

Finally, we discuss the possible implication of incorporating strategic consideration into our model. As shown in the literature of war of attrition, when there are another airline competing in the same market, the airline has additional incentive to delay the announcement. Even if the monopolist problem dictates to announce the cancellation earlier, the possibility of the competitor announcing the cancellation earlier gives her an incentive to delay the announcement and then squeeze the profit. This strategic consideration of business stealing effect is likely to result in the delay of announcement. Our empirical analysis aims to capture this strategic consideration.

4.2 Empirical framework and Results

In this subsection, we provide results of our analysis of airlines' cancellation behavior during the pandemic.

First, we examine the relationship between cancellation rate and COVID-19 infection risk, relevant policies, and market structure. Consider the following reduced-form regression equation:

$$y_{jmt\tau} = \beta^{covid} x^{covid}_{jmt\tau} + \beta^{policy} x^{policy}_{jmt\tau} + \beta^{mkt} x^{mkt}_{jmt\tau} + \Gamma_{jmt\tau} + u_{jmt\tau} \tag{2}$$

where j, m, t, and τ stand for firm, market (origin-destination), departure date, and announcement date. We let y represent cancellation rate for each airline-OD-departure date, which is announced at date τ. Notice that we explicitly consider the distinction between announcement and departure date τ and t. This allows us to control the variables that are known at the time of announcement, while taking into account the variables that can affect the decision-making process for specific departure dates (e.g., seasonality of the demand).

For regressors, we first include measures of infectious risk, $x^{covid}_{jmt\tau}$, to investigate the relationship between infection expansion and cancellations. The construction of this variable follows Kawaguchi, Kodama, and Tanaka (2021). From the number of reported cases published by local governments, we calculate the COVID infection risks, by dividing one-week average of infection cases of each prefecture by its population. Those prefecture-level measures are matched with airports' location. Since each observation consists of an origin-destination pair, we add the average cases of both origin and destination prefectures in our model. We also construct geometric mean of origin cases and destination cases, following the airline literature's convention of accounting for a market size of ODs[8].

Another group of relevant regressors, $x^{policy}_{jmt\tau}$ consist of variables related to two policies described in the previous section. For emergency declaration, we construct four binary indicators corresponding to four different phases of the declaration. For Goto campaign, we consider two indicators: one takes 1 if on the announcement date (τ), airlines are aware of the implementation of the policy. We term this indicator as Goto (announcement). The other indicator takes value 1 if the Goto campaign is implemented in the market at time τ, which is termed as Goto (in effect). Table A.3 shows the formal definition and scope of those variables.

The third variable of interest is x^{mkt}, which captures the market structure of each route. For each market, we construct an indicator Duopoly, taking value 1 if two airlines operate in the market and value 0 otherwise. We also include interaction between this indicator and dummy variables $1_{\{t-\tau\leq 7\}}$ and $1_{\{t-\tau\in(7,14]\}}$ that measure the duration between announcement and departure date. Motivated by Figure 5 and the theory of war of attrition, we expect that the strategic incentives leads to heterogenous effects of market structure in different durations.

Γ stands for the fixed effects of seasonality (month), route size (number of flights), and date of announcement, all interacted with firm identities. Instead of including OD-level fixed effect, which precluses time-invariant covariates including market structure, we use route-size fixed effect to control the unobserved heterogeneity across different markets.

The results of the regression are shown in Table 4. In column (1), we show a parsimonious specification with only geometric mean of infection risks representing COVID-19 infection risk.

8. See Berry and Jia (2010) and Doi and Ohashi (2019), for example.

Table 4: Results of Cancellation Rate Regression

	FE			IV	
	(1)	(2)	(3)	(4)	(5)
Covid ($x^{covid}_{jmt\tau}$)					
Infection risk at τ (dep)		0.027**	0.048**	0.621**	0.614**
		(0.013)	(0.023)	(0.299)	(0.229)
Infection risk at τ (arr)		0.022**	0.045**	0.683**	0.692**
		(0.012)	(0.021)	(0.338)	(0.264)
Infection risk at τ (dep) $\times\tau$		−0.000**	−0.000*	−0.004**	−0.004**
		(0.000)	(0.000)	(0.002)	(0.002)
Infection risk at τ (arr) $\times\tau$		−0.000**	−0.000*	−0.004**	−0.004**
		(0.000)	(0.000)	(0.002)	(0.002)
Geometric mean of	−0.038	−0.073*	−0.108**		
Infection risks at τ	(0.025)	(0.043)	(0.056)		
Infection risk at t (dep)			−0.038*		0.001
			(0.022)		(0.038)
Infection risk at t (arr)			−0.037**		−0.013
			(0.022)		(0.032)
Policy ($x^{policy}_{jmt\tau}$)					
Em Declaration (ph1)	0.013	0.004	0.005	−0.128*	−0.131**
	(0.021)	(0.005)	(0.005)	(0.071)	(0.063)
Em Declaration (ph2)	0.013**	0.000	0.000	−0.003	−0.002
	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)
Em Declaration (ph4)	0.054**	0.053**	0.062**	0.071***	0.070***
	(0.016)	(0.004)	(0.004)	(0.007)	(0.007)
Goto Campaign (announcement)	−0.036**	−0.036**	−0.033**	−0.036***	−0.030*
	(0.011)	(0.001)	(0.001)	(0.007)	(0.017)
Goto Campaign (in effect)	0.011	0.012	0.005	0.008	0.015
	(0.017)	(0.020)	(0.020)	(0.047)	(0.025)
Market Structure ($x^{mkt}_{jmt\tau}$)					
Duopoly Route	−0.009**	−0.005**	−0.011**	−0.012**	−0.013***
	(0.004)	(0.002)	(0.001)	(0.005)	(0.004)
Duopoly Route $\times 1_{\{t-\tau\leq 7\}}$		0.038*	0.038**	−0.002	−0.001
		(0.006)	(0.006)	(0.008)	(0.007)
Duopoly Route $\times 1_{\{7<t-\tau\geq 14\}}$		0.005	0.006	0.007*	0.007*
		(0.020)	(0.018)	(0.005)	(0.004)
Observations	60658	60658	60658	56787	56787
FE: Announcement Date	Yes	Yes	Yes	Yes	Yes
FE: Route Size	Yes	Yes	Yes	Yes	Yes
FE: Month of flight	Yes	Yes	Yes	Yes	Yes

*Note:*This table shows the results of fixed effect regression Eq.(2). All fixed effects are interacted with firm identity. Standard errors are clustered within OD and announcement date. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Column (2) and (3) add the infection risks at origin and destination airports on preannouncement date and departure date, respectively.

First, the result in columns (2) and (3) shows that the infection risks are associated with an increased cancellation rate, as the estimates of infection risks on the preannouncement date are positively significant. At the same time, we found that the degree of correlation is decreasing as time passes, which is shown in the negative sign of the interaction of infection risks and elapsed time. This result is consistent with both the intuition pandemic playing a role of negative demand shock and the data of seemingly opposite movement of cancellation rates and infection numbers in Figure 1.

One concern about the result on COVID-19 variables is that it might suffer from the endogeneity problem caused by omitted variables. In theory, the primary determinants of the cancellation decision is the demand shocks observed by airlines, while the infection variables work as a proxy. This concern is especially prominent when we look at the coefficients of infection risks on the departure date, which are negative and (marginally) significant. Although it can be interpreted by airlines consistent forecast error resulting in more cancellations when pandemic is more severe, it is also likely that the omitted variable bias is driving those estimates. To address this concern, we use instrumental variable (IV) strategy.

Our IVs consist of mobility measures published by Google Community Mobility Reports. The report measures the geographical trend in people's movement in six categories: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential. They measure the volume of total visitors to each place, thus correlating with the future COVID-19 spread. Given the locality of those mobility measures and the nature of distant airtravel, we claim that our IV is exogenous to the unobserved demand- and supply-shocks observed by airlines. This holds more likely once we take lags of those mobility indices from the preannouncement date. We use 14 days lag of the mobility indices, and we also exclude the *retail and recreation index* for robustness. We retrieve prefecture-level mobility indices from the COVID standard dataset of Nakata and Okamoto (2020).

The result of IV regression is shown in column (4) and (5) in Table 4. Compared to the estimates in columns (2) and (3), we see a significant increase in the size of coefficients, which indicates the prominence of the bias. The coefficients of infection risks on departure date are now insignificant, which also suggest the omitted variable bias. The insignificance result is also reasonable given that the future infectious situation is not observed at the time of announcement.

For the first-stage results, the F-statistcs are sufficeintly large, as it exceeds 100 for most of the endogenous regressors, so we believe that we believe our instruments do not suffer weak-IV problem. Over-identification tests are not rejected, which suggests that the policy variables can seen as orthogonal to demand shocks. Those first-stage results are shown in Appendix.

We do a simple back-of-the-envelop calculation to understand the magnitude of the impact of COVID-19 infection risks on cancellation rates. In April, when a median cancellation rate is 33%, an increase of infection risk from the median value by 30% would raise the cancellation rate by 9.7%. As the significant coefficients of the time-interaction terms suggest, the impact of infection risks is decreasing as time passes. In August, when the median cancellation rate is 20%, an increase of infection risk from the median value by 30% would raise the cancellation rate by only 0.4%

We find heterogenous effects of policy variables shown in the next chunk of rows. The Emergency declaration did not have significantly positive impact on cancellation rates until the last period, where it was extended for about two weeks in selective prefectures. One interpretation is that this policy deployment was expected except for the last one. Note that the earlier declarations were made in early and mid April, amid the stark rise of the pandemic. If airlines were aware of the possibility of such lock down measures, they might have already adjusted their operations before the policy deployment, while the last extension amid the declining infection numbers came as a surprise. This interpretation also explains negative impact of the phase 1 declaration, which is significant in columns (3) and (4), as a airlines increasing operation for preemption of the future lockdown.

The result of Goto campaign is also consistent with this expectation-based interpretation. The announcement of the policy had a negative impact on cancellation rates, which can be considered as the expected rise in demand in the future period. The implementation of the policy did not have a significant impact. This result is also inline with the documental evidence of press releases of one of the airlines, which states in July that it expects the demand to recover in August thanks to the Goto campaign, but later in August it states that the demand did not recover as expected.

Finally the result shows that overall cancellation rates are lower in duopoly markets by around 1%. This is consistent with the economic intuition that duopoly markets are more competitive than monopoly markets, thus leading to lower cancellation rates. As to the interaction terms with the duration, however, we find ambiguous results. Some of the coefficients are positively significant at 10% level, which suggests that more cancellations are made in shorter duration in duopoly markets. This is in line with the implication of war of attrition, although most of the coefficients are not significant. We cannot claim that the results here support the airlines practice of war of attrition.

4.3 Duration analysis

To further examine the relationship between COVID-19 infection and cancellation behavior, we conduct survival analysis. Our aim is to understand the dynamics of cancellation behavior, which is not captured by the regression analysis with an emphasis on the duration between announcement and departure date.

We view a flight cancellation as a probabilistic event that can happen during their *lifetime*, defined as the duration. The estimator of the survival probability, $S(t-\tau)$, helps us understand how likely airlines are to cancel flights at a given timing.

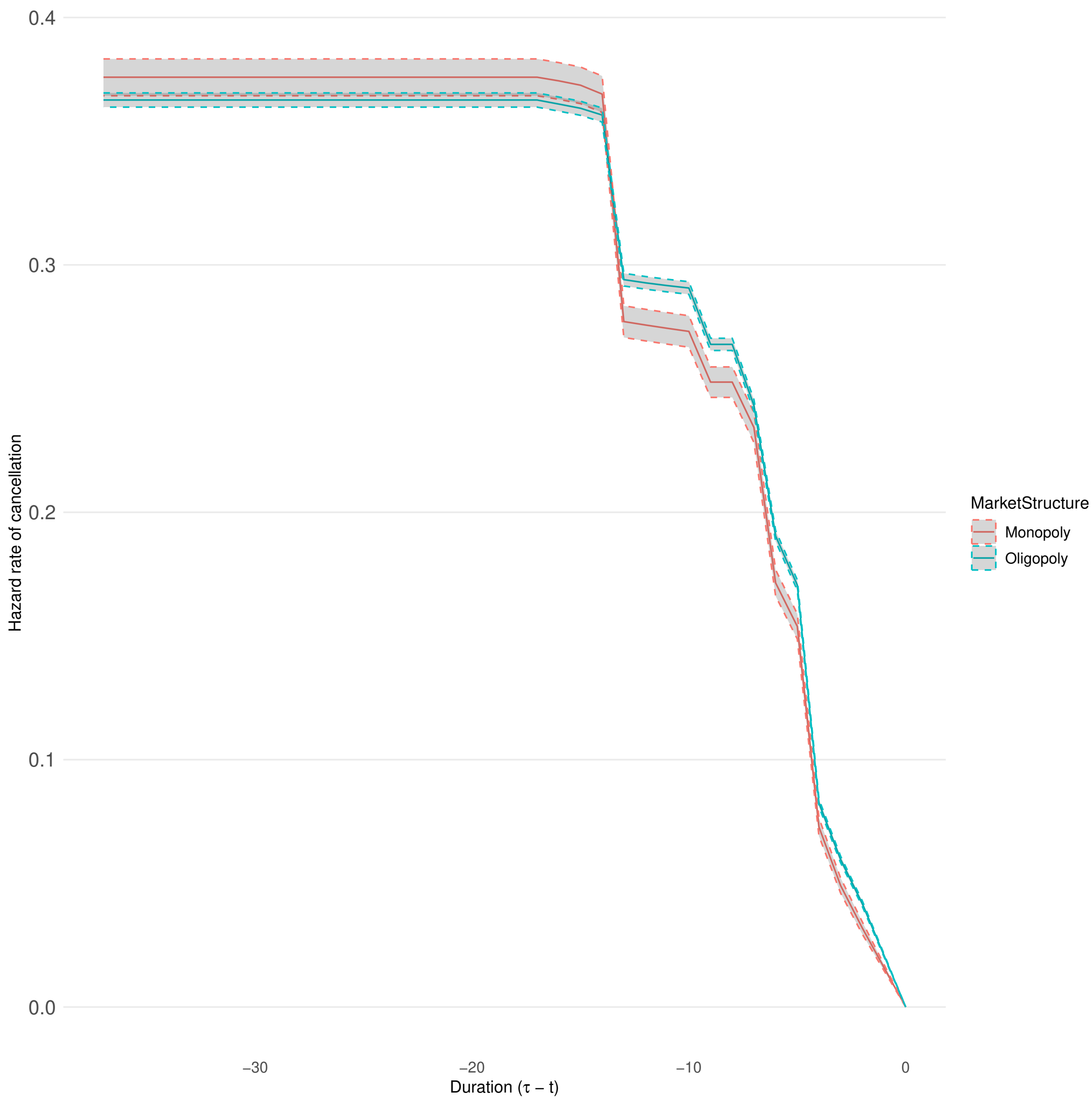
We restrict our attention to the observations before June 2020 for two reasons. First, restricting our sample this period allows us to control the uncertainty to some degree. As the theoretical model we present above suggests, the uncertainty of the pandemic is a key determinant of the cancellation behavior. We suspect that this uncertainty related to the pandemic varies over time. Second, subsampling allows us to avoid the computational burden significantly. Unlike the previous regressions, survival analysis requires us to consider all flights scheduled on each day, which leads to an exploding data size as we include more dates.

We first estimate the Kaplan-Meier curve of the hazard ratio of cancellation event (Kaplan and Meier 1958). The hazard function is the probability of cancellation at a given length of duration, or distance from the departure date to the departure date, conditional on the event that the flight is not canceled up to that point. Figure 6 shows that the hazard ratio of monopoly routes is higher up to two weeks before the departure date, that of duopoly routes gets higher after that point, and then the two become identical around 5 days before the departure date. This suggests that the airlines in monopoly routes are more likely to cancel flights in advance, while the airlines in duopoly routes are more likely to cancel flights in later periods. The difference in the dynamics of cancellation behavior can be understood as the strategic delay.

We also conduct the log-rank test (Harrington and Fleming 1982) to tests the hypothesis that the two Kaplan Meier curves follow the same stochastic process. The result, shown in panel A of Table 5, rejects the hypothesis at 5% level. We conclude that the dynamics of cancellation behavior is statistically different between monopoly and duopoly routes.

While these results indicate the practice of strategic delay, we cannot take this difference as the evidence of strategic interaction, as it might be driven by the difference in other variables such as infection risks. To get a precise estimate of the impact of duopoly on the dynamics of cancellation behavior, we estimate the Cox proportional hazard model in Eq. (3).

Figure 6: Kaplan-Meier curve of hazard ratio of cancellation



Note: The figure shows the Kaplan-Meier curve of the hazard ratio of cancellation of flights in monopoly and duopoly markets. The hazard ratio is the probability of cancellation at a given length of duration, or distance from the departure date, conditional on the event that the flight is not canceled up to that point. The shaded area represents the 95% confidence interval.

$$h(t) = h_0(t) \exp(\alpha \times 1_{Duopoly} + \beta' \mathbf{x}_t) \tag{3}$$

where $h(t)$ is the hazard function indicating the risk of the cancellation announced at time t.

Table 5: Results of survival analysis

	A: log-rank test
Test Statistics	4.5**
(p-value; degree of freedom)	(0.03; 1)
	B: Cox hazard
Duopoly	0.655***
	(0.187)
Controls	
Time FE	Yes
Departure FE	Yes
Arrival FE	Yes
COVID risks	Yes

Note: The upper panel shows the result of the log-rank test. The null hypothesis is the two K-M curves between monopoly and duopoly routes are the same. The lower panel shows the estimates of Cox proportional hazard model. We report the hazard ratio of the duopoly indicator, $\exp(\alpha)$. Robust standard errors clustered at OD-announcement date level are in the parentheses. We restrict our sample within the observations before June 2020.

Note that we abuse the notation to let t denote the survival time. h_0 is the baseline hazard, which captures the individual heterogeneity. $\mathbf{x}$'s include controls: infection risks and fixed effects of firm, date, and departure- and arrival-prefecture fixed effects. Panel B in Table 5 shows the hazard ratio of duopoly indicator, $\exp(\alpha)$. As shown below, this value represents the exact rate of the hazard probabilities between a monopoly route and a duopoly route. The estimate suggests the hazard ratio is significantly lower than 1 and the airlines in duopoly routes are less likely to cancel flights than those in monopoly routes by around 35%.

$$\begin{aligned} \frac{\lambda(t \mid x, \text{Duopoly})}{\lambda(t \mid x, \text{Monopoly})} &= \frac{h_0(t) \exp(\alpha + \beta' \mathbf{x}_t)}{h_0(t) \exp(\beta' \mathbf{x}_t)} \\ &= \exp(\alpha) \end{aligned}$$

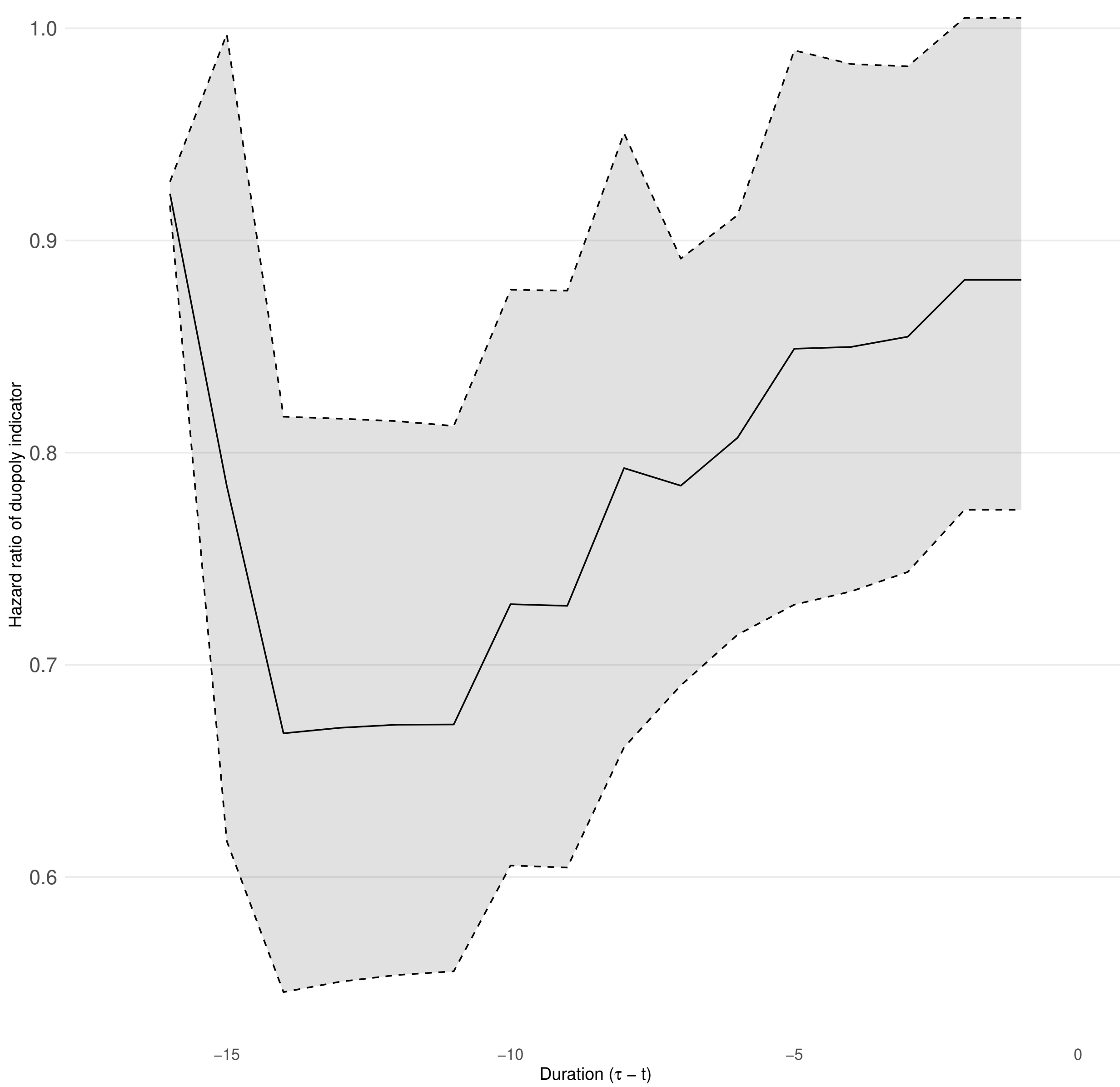
To take a closer look at the dynamics of strategic incentive, we also estimate Eq. (3) with the coefficient of the duopoly indicator, α, varying over time. The result is shown in Figure 7. The figure shows that the hazard ratio of duopoly indicator follows a U-shaped pattern, where it decreases from 0.9 to 0.7 around 14 days before the departure date, and then increases teadily towards 0.9. This rising trend is consistent with the prediction of the war of attrition. As the time passes, airlines incentive to wait diminishes since the probability of the opponent also dminishes. Strategic delay is most prominent around two weeks to one week before the departure date.

The steady increase of the hazard ratio is somewhat in contrast with the result of the war of attrition literature such as Takahashi (2015). This is because the study of war of attrition focuses on the firms' entry/exit behavior. Once the firm exits the market, it cannot re-enter nor any products of that firm does not remain in the market. In our setting, however, the airlines can cancel flights multiple times, and even though they announce some cancellation, there remains some flights in the market. Such features in our setting can be a reason for the steady increase of the hazard ratio.

5 Conclusion

In this study, we examine the strategic interaction between airlines in the context of flight cancellation decisions during the early period of the Covid-19 pandemic. We find that the infection risk significantly influences the airlines' decisions to cancel flights. Specifically, an increase in the infection risk by 30% is correlated with a 10% rise in the cancellation rate during the early period of the pandemic. Additionally, our results reveal that strategic interaction also relates to the dynamics of flight cancellation decisions. The hazard rate of cancellation event is more than 30% lower in duopoly market, while it gets closer to that of monopoly market as the departure date approaches, which is in line with the implication of the war of attrition.

Figure 7: Time-varying coefficient of duopoly indicator



Note: The figure shows the time-varying coefficient of the duopoly indicator in the Cox proportional hazard model. The shaded area represents the 95% confidence interval. Standard errors are clustered at the OD-announcement date level.

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Appendix A Additional Tables

This section provides supplementary tables and figures that are not included in the main text.

Tabel A.1 shows the result of the regression of the posted fares on the COVID-19 infection risks/relevant policy variables. Abusing the notation in Eq. 2, we write the regression equation as

$$Price_{jmt\tau} = \beta^{covid} x^{covid}_{jmt\tau} + \beta^{policy} x^{policy}_{jmt\tau} + \Gamma_{jmt\tau} + u_{jmt\tau} \tag{4}$$

where j refers to the ticket (consisting of airline, ticket type, and flight class), m refers to the market (OD), and t refers to the departure date. τ refers to the date of observation, which is 28, 7, and 3 days prior to the departure date. $Price_{jmt\tau}$ is the fare of the ticket j in market m departing on date t, posted on the date τ. Unlike the studies on the dynamic pricing of airlines, we do not consider the dynamics of pricing represented by the relationship of prices between different dates.

Table A.1: Results of price regressions

Periods:	All (1)	1st wave (2)	2nd and later (3)
Infection risk (dep)	132.801	−22.325	110.045
	(201.843)	(311.491)	(159.389)
Infection risk (arr)	373.281	431.629	157.547
	(221.362)	(325.812)	(262.470)
Em Declaration (ph2)	201.655	233.865*	
	(127.258)	(116.869)	
Em Declaration (ph4)	233.966	147.507	
	(190.901)	(204.366)	
Goto Campaign (announcement)	1317.771*	1012.403*	
	(714.067)	(514.111)	
Goto Campaign (in effect)	−250.385	380.185	−954.582
	(311.180)	(418.160)	(549.453)

Note: This table shows the results of price regression. The regression is based on Eq.(2), while we replace the dependent variable with posted prices. We also include additional fixed effects: ticket type (round trip, discount, or business) and flight class (first or not). All fixed effects are interacted with firm identity. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table A.3 shows the definition of the policy variables used in the main text. The prefectures under the emergency state in the first phase of declaration are Tokyo, Kanagawa, Saitama, Chiba, Osaka, Hyogo, and Fukuoka. The prefectures under the emergency state in the last phase of the declaration are Hokkaido, Tokyo, Kanagawa, Saitama, Chiba, Osaka, Hyogo, and Fukuoka. The prefectures under the emergency state in the second and third phases of the declaration are all

Table A.2: The proportion of the flights of which cancellation is announced

Month	Preannounced cancellations(%)
Apr	95.0
May	95.7
Jun	95.1
Jul	95.2
Aug	95.0
Sep	88.2
Oct	94.1
Nov	93.2

Note: This table shows the share of the flights of which cancellation is announced in each month of 2020. The drop in the share in September is primarily due to the typhoon hitting Kyushu region, south-west parts of Japan at the beginning of the month.

Table A.3: Definition of variables

COVID variables		
Infection risk at s	Weekly cases on day s divided by the number of population	
Policy variables	Timing	Geography
Em declaration (ph 1)	April 7 to April 15	7 prefectures (including Tokyo)
Em declaration (ph 2)	April 16 to May 3	All prefectures
Em declaration (ph 3)	May 4 to May 13	All prefectures
Em declaration (ph 4)	May 14 to May 25	8 prefectures
Goto Campaign (announcement)	June 16 to July 9	All prefectures
Goto Campaign (in effect)	from July 10	All prefecture (with some exception)

Note: Timing is measured in terms of announcement date (τ). For the implementation of Goto Campaign, Tokyo was excluded from the campaign until October 1, 2020.

prefectures in Japan.

Appendix B Theoretical Model

This section provides a detailed description of our theoretical model of monopolist airline's dynamic decision of flight cancellation.

As in the main text, we consider a monopolist airline that operates on a route and decides when to announce and how many flights to cancel, i.e., announcement date $\tau \in [0, t]$ and cancellation rate $f \in [0, 1]$. The airline's ex-post profit is a function of her choice of the cancellation rate and the demand shock ε_t, $\pi(f, \varepsilon_t)$. We assume the airline's ex-post profit function is given by

$$\pi(f, \varepsilon) = (a - \varepsilon)f - bf^2$$

where $a, b > 0$ are the parameters determining the curvature of the profit function. The parametric form assumption imposes a certain restriction on how the demand shock affects the profitablity. As if affects the profit linearly, one interpretation is that the effect of demand shock is uniform across all flights within the route and canceling one flight is equivalent to cancel any other flight.

The information structure is given by Eq. (1). We continue to assume $\sigma' < 0$. We further assume $\sigma'' > 0$. They imply that while the airline can increase the precision of her signal by waiting, the marginal gain decreases over time. We presume this is reasonable.

The airline's decision is two-stage. In the first stage, the airline decides when to announce the cancellation rate, τ. In the second stage, which occurs on date τ, the airline decides the cancellation rate f, observing η_τ. The airline is assumed to maximize her expected profit. We start with the second stage decision to solve the model.

Given the announcement date τ, the airline's expected profit is given by

$$\max_{f \in [0,1]} \mathbb{E}[\pi(f, \varepsilon_\tau) | \eta_\tau]$$

Notice that the bivariate distribution of $(\varepsilon_\tau, \eta_\tau)$ yields

$$\mathbb{E}[\pi(f, \varepsilon_\tau) | \eta_\tau] = \left[a - \left(\mu_\varepsilon + \frac{\rho}{\sigma(\tau)}(\eta_\tau - \mu_\eta)\right)\right] f - bf^2$$

Hence, the optimal cancellation rate, f^* is given by the first-order condition

$$\begin{aligned} 0 &= a - \left(\mu_\varepsilon + \frac{\rho}{\sigma(\tau)}(\eta_\tau - \mu_\eta)\right) - 2bf^* \\ f^* &= \frac{a - \left(\mu_\varepsilon + \frac{\rho}{\sigma(\tau)}(\eta_\tau - \mu_\eta)\right)}{2b} \end{aligned}$$

Note that second-order condition is satisified as long as $b > 0$. Assuming inner solution, we get the first proposition:

Proposition 1. *The announced cancellation rate, $1 - f^*$, is increasing in the infection risk on the announcement date, η_τ.*

Next, we solve the first stage decision. The airline's expected profit at the first stage is given by

$$\max_{\tau \in [0,t]} \mathbb{E}[\pi(f^*, \varepsilon_\tau)|\eta_\tau] - C(\tau)$$

The first-order derivative of the expected profit function is given by

$$\begin{aligned} \frac{d}{d\tau}\mathbb{E}[\pi(f^*, \varepsilon_\tau)|\eta_\tau] - C'(\tau) &= f^* \frac{d}{d\tau}\mathbb{E}[\varepsilon_\tau|\eta_\tau] - C'(\tau) \\ &= f^* \left(\rho \frac{\sigma'(\tau)}{\sigma(\tau)^2}(\eta_\tau - \mu_\eta) \right) - C'(\tau) \end{aligned} \tag{5}$$

Given our parametric assumptions $\sigma' < 0, \rho > 0, C' > 0$, the optimal announcement timing would be 0 if $\eta_\tau \geq \mu_\epsilon$, i.e., the infection signal is higher than expected (*bad news*).

We focus on the case where $\eta_\tau < \mu_\eta$ (*good news*) and the optimal τ falls in $(0, t)$. In this case, the optimal announcement timing is given by the first-order condition[9]. We can interpret the first term of Eq. (5) as the marginal gain of waiting. When the signal tells that the concurrent infection risk is more or less better than expected, then the airline has some hope that the future demand situation can be also improved, and confirming such a news by delaying a decision pays off. The second term is the marginal cost of waiting. The optimal announcement timing is determined by the trade-off between the two terms.

Notice that f^* is decreasing in σ. Given this observation, we have the next proposition that characterizes the comparative static of optimal announcement timing in terms of the uncertainty of the signal of infection risk, $\sigma(\tau)$.

Proposition 2. *Given that $\eta_\tau < \mu_\eta$, the optimal announcement timing, τ^*, is decreasing in the uncertainty of the signal, $\sigma(\tau)$. That is, the airline is more likely to quicken the announcement when she is more uncertain about the current state.*

9. The second-order condition is satisified thanks to our assumptions on σ' and σ''.

Intuitively speaking, when we increase only σ while fixing η_τ and σ', the marginal gain of waiting decreases as the value of confirming good news, $\rho\frac{\sigma'(\tau)}{\sigma(\tau)^2}(\eta_\tau - \mu_\eta)$, decreases. Furthermore, the optimal flight volume f^* also decreases as the good news is less reliable. The cost of delay does not change. Hence, the airline is more likely to announce the cancellation rate earlier.