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Empirical Analysis of the Codeshare Effect on Airline Market Competition and Product Quality

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Empirical analysis of the codeshare effect on airline market competition and product quality [1]

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Abstract

This paper examines the economic consequences of code-sharing agreements (CSA) in the airline market. CSA can be viewed as a vertical contract between airlines, which sometimes co-own the code-shared flights. Our structural model aims to understand how and to what extent CSA distorts market competition among airlines. With an application to Japanese domestic airlines, structural estimates of our demand and supply models indicate that CSA would significantly lessen market competition, by sharing increased revenues from raised fares. We further extend our model to consider endogenous product quality. Although the loss of consumer welfare due to CSA is alleviated by enhanced product quality, the anti-competitive effect of CSA is persistent.

Keywords: Codeshare; Airline industry; Horizontal merger; Structural estimation
JEL classification: L11, L13, L93, L41, C51

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1 Introduction

Code-sharing agreement (CSA) has been a prominent form of airlines alliance in the past two decades. While airlines claim CSA confers benefits of extended networks beyond what a single airline could offer, authorities raise concerns with anti-competitive effects brought by CSA. Several empirical studies investigate the impact of CSA on market competition and consumer welfare. However, most of them solely focus on fares, partially because of the difficulty in measuring the product quality. Hence, the implication of CSA for the quality of air-travel service and market competition is still unclear despite the above arguments.

In this paper, we investigate the economic consequences of CSA on airlines' incentive, market outcomes, and consumer welfare. We particularly focus on two characteristics of our data. First, the form of CSAs is relatively homogeneous, making the theoretical analysis simple and more consistent. Basically CSA can be implemented in different ways across each contract such as the quota of seats assigned to the partner. If the data at hand contains several forms of CSA, the rigorous study will suffer from complicated details and the larger parameter space. Contrary, in our data, regulations require all airlines involved in CSA to sell the tickets of code-shared flights. An introduction of CSA thus results in a combination of vertical relationship and partial ownership between partners uniquely across markets.

Second, we focus on flight frequency as a measure of product quality and regard it as an endogenous object. Introducing endogenous quality alter the incentives of airlines. The implication of CSA in this situation is ex-ante ambiguous: It can aggravate the anti-competitive effect by enhancing collusive behaviors, or have pro-competitive effect by giving incentives to compete for additional revenue.

Our structural model incorporates these two features to study the mechanism of CSA and its implication for market outcomes. The model consists of demand and supply side, and describe the market competition as a Bertrand competition of differentiated products. Extending the standard formulation, our model regards the fare and flight frequency as equilibrium objects, determined endogenously through demand and supply interaction. In addition, on the supply side, we view CSA as a contract that induces a vertical relationship and partial ownership between the partners. Because the change in the ownership structure affects the airlines' incentive for both code-shared products and non code-shared, products, or single-carrier products, the determination of fare and quality differs from the standard Bertrand fashion.

We apply the structural model to the data set constructed from Japanese domestic airline statistics. In particular, the timetable data provides detailed information including flight frequency and identity of code-shared flights. This detailed information facilitates our estimation procedure. The airline market in Japan is suitable for studing CSA implication in two ways. First, all code-sharing agreements are uniform in that the compositions of agreement partners have few patterns and the contract forms is the same, which simplifies the model analysis. Second, The government regulations on the code-sharing practices are also useful in the estimation part.

The estimation result consists of the demand and supply side. The demand model is based on the random coefficient model, which shows consistent results with the past empirical studies. It also implies that the flight frequency is an important component in consumers' utility. The supply-side model consists of the marginal cost functions and a code-sharing parameter, which governs the level of codeshare. The estimated code-sharing parameters are around 0.09 to 0.4, i.e., a partner airline of CSA sells around 10 to 40% percentage of tickets of a code-shared flight, while it does not carry out any actual operation.

Finally, using the estimated model, we conduct counterfactual simulations to quantify the impact of code-sharing agreements. We calculate the market fares, flight frequencies, and consumer welfare where the agreements does not affect competition. According to the simulation results, if the flight frequencies are fixed, introducing CSA increases fares by 15% and lowers the consumer welfare by 6%. Once we endogenize the flight frequency, the flight frequency increases on average by 6% and alleviates the consumer welfare loss. However, the anti-competitive effect of CSA via large fare raise is strong, reducing the social surplus. To fruther investigate the impact of CSA, we decompose the codeshare effect into several parts. We find that the horizontal partial ownership amounts to half of the fare increase caused by CSA, and the airlines engaging in CSA choose to impose higher price-cost margins than Non-CSA airlines.

Related Literature

This study relates to the literature on of domestic code-sharing agreement. Many of the existing study focus on the effect on fares and consequences to the social welfare. While early studies including Ito and Lee (2007) and Gayle (2008) employed reduced-form approach on the price effect, several studies have examined the anti-competitive effect of code-sharing agreement using structural estimation methods. Shen (2017) builds a structural model of U.S. domestic codeshare, regarding CSA as horizontal revenue-sharing rule. He explicitly estimates the degree of code-sharing, i.e., how much revenue the agreement partners share each other. Gayle (2013) focuses on the vertical relationship entailed by CSA to study the competitive effect of codeshare in the context of double marginalization. Our study can be understood as a extension of both studies in that we build a model of both horizontal revenue share and vertical relationship.

In addition to such modeling strategies, our study also relates to two strands of literature in industrial organization. The first one is the vertical relationship. Apart from codeshare, several empirical studies have been conducted to examine the effect of vertical relationship, such as Villas-Boas (2007), Bonnet and Dubois (2010), and Crawford et al. (2018). In spirit of those research, we also focus on the problem of double marginalization caused by vertical transaction, and its welfare effect.

The second strand of literature our study also contributes to is the on product quality. Several empirical studies have been conducted recently to investigate the codeshare effect on product quality. Brueckner and Luo (2014) estimates the reduced-form reaction function to quantify the impact of strategic interaction between airlines on the product quality, represented by flight frequency. Doi and Ohashi (2019) also use flight frequency as product quality measure to carry out the structural estimation and post-merger evaluation in terms of fare, frequency, and social welfare. Our approach resembles to theirs in the treatment of flight frequency. In the context of codeshare, several empirical studies employ reduce-form methods to examine the impact on product quality. Gayle and Thomas (2015) use international airline data to examine the alliances, which includes various forms of codeshare, in relation to routing quality. Their result implies that the alliances enhance the routing quality. In US domestic market, Yimga (2022) uses path quality as a quality measure and also finds that code-sharing agreement leads to quality improvement in some cases. To our knowledge, in the context of codeshare, the present study is the first empirical research to employ a structural model to quantify the codeshare effect on product quality choice. We aims to provide insights from structural approach.

The rest of the paper is organized as follows. Section 2 introduces institutional details. Section 3 provides data used in the structural estimation. Section 4 describes the structural model and identification strategy. Section 5 shows estimation results. Section 6 presents our counterfactual simulation results. Section 7 concludes.

2 Institutional Background

This section provides an overview of the Japanese domestic airline market in relation to CSA. CSA in Japan has a specific form: either of the two predominant incumbent airlines always involves in marketing activity of code-shared flights, and their quota of seats are under regulatory restriction. Also, most of the CSAs are tied with capital relationships between airlines, which is supposed to enhance between-airline cooperation.

2.1 Code-sharing practice in Japan

Japanese domestic airlines have been signing and expanding the code-sharing agreements during the past decade. Figure 1 shows the evolution of the number of domestic routes where some airlines make CSAs from 2011 to 2018. Compared with the number of overall domestic routes, which steadily increases, that of the routes with code-shared flights exhibits sharp increase especially in the early 2010s.

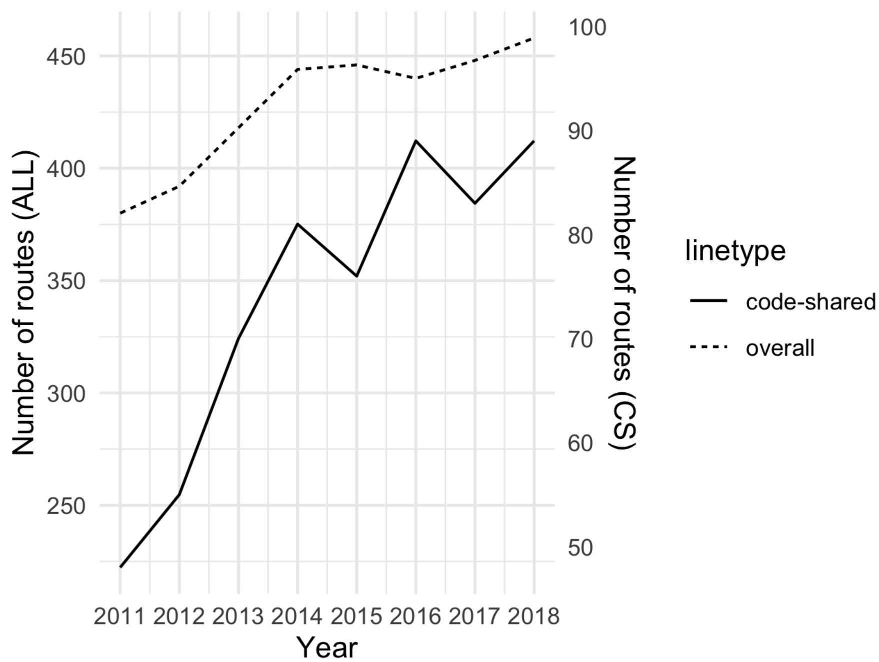


Figure 1: The evolution of the number of domestic routes containing code-sharing agreements

We focus on three notable features of CSA in domestic Japan during this period. The first is how they cooperate in an agreement. During this period, one agreement partner operates the aircraft for the code-shared aviation service, and also sells a fraction of seats of this aircraft by her own. The other partner is responsible for the rest of the seats, and tries to sell them by his pricing policy. In other word, there exists a clear distinction between the two partners in that one airline undertakes the operation of aircraft[1].

The second important detail is the identity of the airlines involving in CSA. In any agreement during the sampling period, either of the two incumbent airlines, ANA and JAL[2], serves as one of the partners. Also, they always confine to marketing activity in

1. There are a different form of code-sharing agreement. They are beyond the scope of this paper.
2. We use three-letter code to represent airline companies throughout this paper.

any agreement, i.e., they do not operate any aircraft as a code-shared flight.

Also, any agreement JAL is engaging in takes place where the market is monopoly of the partner airline. Each partner provides aviation service and the market has no other competing airlines, nor JAL. This monopoly structure is partially because of the market sizes: partners of JAL are regional airlines and they offer flights in small markets. Since the operating airlines are monopoly players, such an agreement does not affect competition competition. Hence, we exclude those agreements from our empirical analysis and concentrate on the agreements involving ANA. That allows us to reduce the dimension of parameters to be estimated.

The third point is the quota of the code-shared seats, i.e., how much ratio of seats each partner undertakes. A major concern on CSA is that it might dampen the competition and harm the consumer surplus, especially when it includes a airline with large market power. Having similar concerns in Japanese market, The Ministry of Land, Infrastructure, Transport, and Tourism (MLIT) imposes legislative restrictions[3] on the quota assigned to the large marketing airlines: ANA and JAL are allowed to sell at most 25% of the total seats of a code-shared flight. MLIT changed this ratio at the beginning of 2013, from 25% to 50%.

We utilize the regulation imposed by MLIT to consider those numbers.

2.2 Airlines in domestic air transportation

This subsection overviews inter-airline relationships during the sampling period. The two incumbents acquire capital stakes of several domestic airlines, which coincides with CSA. This implies the possibility of between-airline cooperation via capital ties and CSA.

To grasp the overview, we describe airlines' relationship in Table A1, in the appendix. Panels A and B refer to the group formed by ANA and JAL, respectively, while C represents a group of airlines without any capital ties. It shows that those two predominant airlines have some voting rights to the most of competitors to some degree.

It can be seen that the capital share distribution has two extremes: some airlines has less than 20% shares owned by the dominant FSCs while the others are almost fully owned. This is due to the regulation imposed by Ministry of Land, Infrastructure, Transport, and Toursim (MLIT), which prohibits airlines from acquiring more than 20% capital shares. From this observation, we regard those airlines with shares owned by ANA/JAL less than 20% as independent competitors. On the other hand, the airlines with owned shares more than 20% are reckoned as subsidiaries. We use this distinction to

3. On Use of New Preferential Quota for Joint Carriage, MLIT (2006)

construct the ownership structure of product market competition later in the modeling section.

3 Data

This section describes the data sets used in the empirical analysis. It is a panel data containing flight-specific information such as origin-destination, fares, departure time, and aircraft size with observations obtained biennially. We look at summary statistics and results of preliminary statistical analysis to probe the market implication of CSA.

The first data is retrieved from published timetable data of domestic air-travel, which allows me to access the microlevel panel data that contains characteristics of each flight operated by an airline on a specific route. The data describes the exact schedule information on quarterly basis, as we can see in the airline website or airport boards. As a hypothetical timetable shown in Table A2, it tells which and when a flight is planned to depart from and arrive at the endpoints with additional information on flight and aircraft ID. It also specifies whether a flight is code-shared by which airline, if it is shared.

The second source is *Traveller Statistics in Domestic Airline Market* published by MLIT, conducted biennially in odd-numbered years from 2011 until 2017. From all the passengers taking a plane on specific dates of November, the survey collects detailed information including fares paid, the rank of seats, the ID of the flight, and whether the ticket is direct or connecting. That enables us to construct microlevel panel data of average fares for each flight, the operating airline, and market. Since this data contains all flights departing on a particular date, we can also construct a flight frequency measure for each period, market, and airline, which is regarded as product quality of the air transportation service. To limit the heterogeneity across passengers, we exclude observations that use first-class seats, connecting flights, or premiere discounts, which account for around 15 to 20 % of the overall sample for each year.

The third is obtained from *the Annual report on Air Transport Statistics*, which is again published by MLIT. The statistics provides the number of passengers conveyed by airlines in most domestic OD pairs on monthly basis. We use this number to create a panel of market-level share data, by combining it with the market size defined as the geometric average of endpoint airports' population. Note that an airport's population is specified as the population of the urban area where the airport is located. The geographical definition and population data is from Kanemoto and Tokuoka (2002)[4]

4. This market size definition follows the procedure of Doi and Ohashi (2019) who empirically investigate Japanese domestic airline.

Combining these three data yields a panel data set with the observation unit being the year- and market- level in 2011, 2013, 2015, and 2017. Since the market share data is available at most route- and airline-specific level, We define a product as a market-airline combination when employing the structural estimation. That is, a consumer evaluate an air-travel service provided by an airline in terms of the day-level characteristics, including average fares across tickets, the daily flight frequency, and the number of flights operated in a peak demand time.

To separately treat the code-shared flights as a product, we use the survey statistics to infer the number of passengers in the code-shared flights. First, we can calculate the ratio of the respondents between the code-shared flights and purely operated flights. Since the survey contains all the passengers in the given survey date, the calculated ratio of respondents in turn allow me to deduce the market share of those two flights.

We also collect additional data required for improving estimation results, such as demand or cost shifters. The cost shifters include jet-fuel spot prices and airport charge fee. The former is obtained from the U.S. Energy Information administration as a kerosene-type jet fuel spot price in U.S. gulf coast, and the latter is retrieved from the MLIT website for state-owned airports, local administrators' legislation records for local airports, and each airport's website for private ones. All fares, prices, and charge fees are deflated using the consumer price index retrieved from OECD database.

Table 1 gives the summary statistics of product characteristics used in demand and supply estimation in the subsequent sections. We divide products based on their relationship to CSA: the left column represents the products whose owner is engaging in CSA in the market, while the right column represents the product without any relationship to CSA. Following the convention of the literature, we define a market as a unique combination of time period and origin-destination. This table helps us understand the feature of our data in relation to CSA.

Many of the product characteristics, including fares, peak-time ratio, aircraft size, and per-flight charges, are similar between the two segments. However, following characteristics exhibit a clear distinction: the number of competitors, market size, and flight frequency. The difference in the first two, the number of competitor and market size, indicates that the CSA are associated with larger market size. Similar pattern is also reported in US domestic market by Gayle (2013).

The higher flight frequency in code-shared markets can be interpreted as a result of their competitive environments: to steal passengers from competitors, airlines tends to increase their product quality. The effect of CSA, however, is not clear from this understanding with aggregated statistics. Airlines engaging CSA may have disincentive from competing, thus inclined to lower the flight frequency. Since we only observe the aggregated values, the statistics does not describe the exact mechanism.

In short, the anti-competitive effect of CSA, if exists, is likely to dampen competitions in large markets, thus harm the consumer welfare. The summary statistics, however, does not provide clear evidence of such effect. That motivates us to conduct preliminary analyses on the market outcomes and CSA.

Table 1: Summary statistics of product level data

	CSA-related	Non-CSA
share	0.003 (0.007)	0.005 (0.003)
market size (millions)	4.435 (4.881)	2.800 (3.619)
fare (1,000 JPY)	22.589 (4.859)	21.535(7.019)
flight frequency	4.201 (3.578)	3.557 (2.894)
code-shared dummy	0.490 (0.231)	0 (0)
peak time ratio	0.163 (0.270)	0.159 (0.228)
aircraft size (weight/ton)	71.331 (45.227)	70.467 (40.799)
aircraft size (#seats)	153.214 (85.107)	151.865 (83.218)
per-flight charge (1,000 JPY)	115.446 (79.324)	100.543 (76.381)
number of operating airlines	2.848 (1.243)	2.016 (1.041)
Observations	389	2,069

Note: The numbers in parentheses are standard deviations. The levels of fares and charges are deflated in constant 2011 JPY, when exchange rate of U.S dollar to JPY was 86.7. The left column corresponds to the products with owners involving in CSA in the market, while the right corresponds to the products with owners not involving in CSA.

3.1 Preliminary analysis on the relationship between codeshare and flight frequency

To further examine the relationship between CSA and market outcomes, we carry out Regression Discontinuity (RD) study in this subsection. Although the graphical representation may suggest anti-competitive effect of CSA, the estimates are insignificant and does not provide conclusive evidence.

RD design requires three key elements: running variable, cutoff, and outcome variable. Putting aside the assumptions for identification, we specify a specific RD design as follows for the present analysis.

- running variable: time (quarter-level measurement unit)

- cutoff: introduction timing of codeshare

- outcome variable: market outcomes

In this design, we aim to capture the impact of CSA on market outcomes. The identification of such effect depends on whether the continuity assumption holds (Cattaneo, Idrobo, and Titiunik 2019). Suppose the number of passengers (market outcome) is sufficiently smooth around the introduction timing of CSA for a given route. Then, if agreements have any impact, the data will reveal discontinuous change in the observed passenger volume. We try three market outcomes: fare, flight frequency, and passenger volume.

Note that our design is not sophisticated in that the change in market outcomes may reflect other causes than CSA. For instance, several agreements arise during the agreement partners' business crisis[5]. In such cases, the introduction of CSA may come in parallel with a decline in passenger volume and flight frequency. The resulting estimates are likely to overstate the impact of CSA. To deal with the concern, we try to adjust such effect by including as much covariates as possible using the covariate-adjustment method (Calonico et al. 2019). The covariates include fixed effect of time, airline, and ODs and product characteristics such as average aircraft size. However, we are not confident in the accuracy the obtained estimates.

Figure 2 shows the graphical representation of the result. The cutoff point, introduction of CSA, is normalized to be zero. And, for all outcomes, the study uses airline-level observations and the triangular kernel function.

From the first two rows, the passenger volume and fare level, We cannot find any prominent difference. Especially, the volatility in the passenger volume makes it difficult to derive a inference from the graphs. For fares, as depicted in the second row, the distribution of fares seem smooth around the cutoff point, while our data does not show significant change at the timing of the agreement.

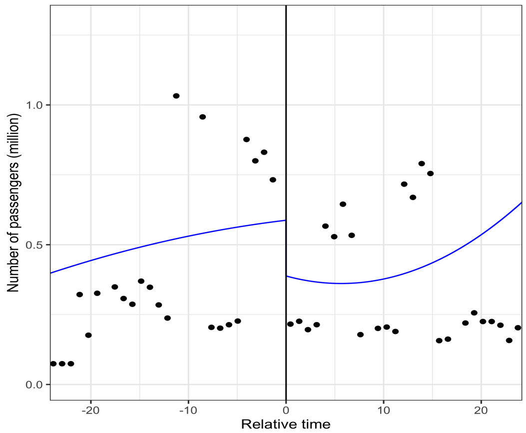
For flight frequency, the third row of Figure 2, we find relatively distinct change. In particular, very after the introduction of code-sharing agreement, the observed frequencies decreases by large amount. Although the estimated coefficient is not significant as in Table 2, this result motives me to focus on flight frequency as well as fare, in relation to code-sharing agreement.

The estimated effects are presented in the Table 2. Each columns corresponds to the right side panels in Figure 2. Although all of them exhibit positive estimate, the standard errors are large. Thus, although there may exist some apparent impact of CSA introduction, the reduce-form analysis does not provide strong support for it.

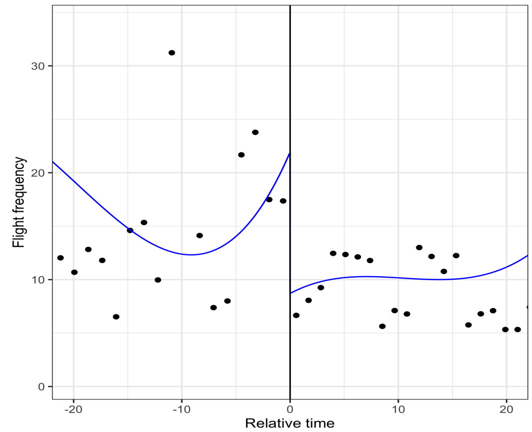
5. An example is between ADO and ANA in around 2000.

Figure 2: Graphic Evidence of codeshare impact on market outcomes from RD

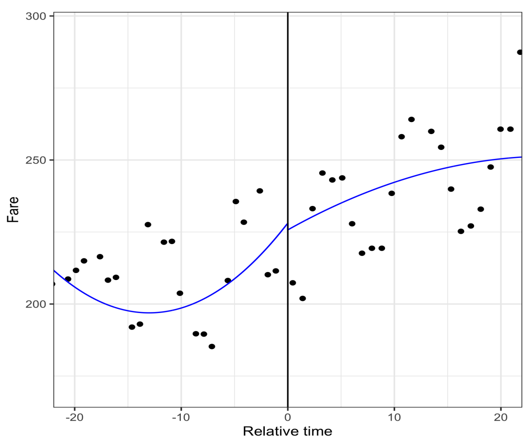
(a) Number of passengers (all competitors)



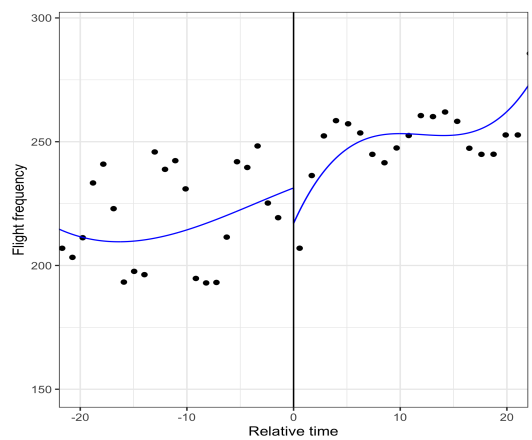
(b) Number of passengers (CSA partners only)



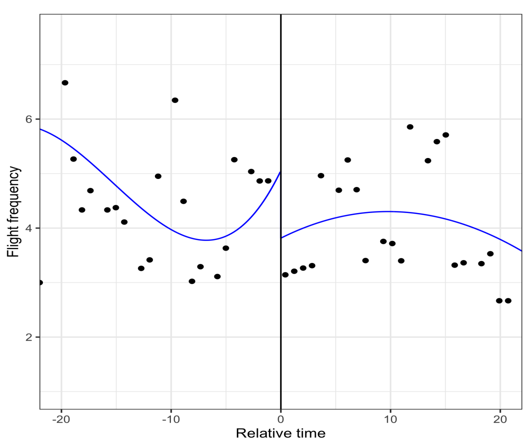
(c) Fare (All competitors)



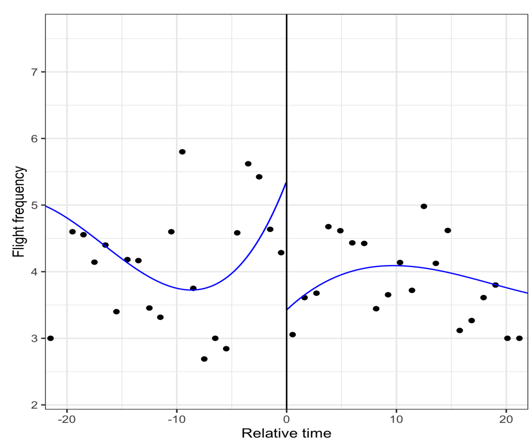
(d) Fare (CSA partners only)



(e) Flight frequency (All competitors)



(f) Flight frequency (CSA partners only)



Note: The horizontal axis represents the relative time to the introduction of CSA, measured at quarter level. The vertical axis represents the market outcomes. Each point represents the average value of the market outcome across airlines, at given time. For covariate adjustment, we include fixed effects of time, airline, and ODs and other product characteristics described in Table 1.

Table 2: RD study of the codeshare effect on flight frequency

outcome variable	passneger volume	fare	flight frequency
codeshare impact	0.001	3.000	-0.551
	(0.121)	(17.565)	(0.492)
kernel	Triangular	Triangular	Triangular
RD specification	Quadratic polynomials	Quadratic polynomials	Cubic polynomials
Number of Observation	1570	1570	1570

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Note: All estimates are obtained by applying covariate-adjustment method of Calonico et al. (2019), where we use covariates of flight characteristics and market characteristics.

4 Methodology

In this section, we describe the structural model used to analyze Japan domestic market and the impact of code-sharing agreements. The model consists of demand side and supply side. For the demand, we utilize the discrete choice framework presented by McFadden (1981). Our model treats both product fares and quality, the flight frequency in our setting, as endogenous variables. Then, we model the supply side as Bertrand competition of differentiated products with several modifications. First, as coherent with the demand-side specification, airlines choose flight frequency as well as fare to maximize their profit. Second, we specifically formulate CSA as an inter-airline agreement that introduce (i) partial ownership and (ii) vertical relationship. share The degree of CSA is represented by an additional unobserved parameter, which represents the quota of seats assigned to partner airlines.

4.1 Demand specification

In this subsection, we describe the demand-side model and estimation strategy. A discrete-choice model is considered with random-coefficient assumption. The flight frequency, perceived as product quality, is considered as endogenous as well as fare.

Following the methodology of those studies on the airline market, including Berry and Jia (2010) and Doi and Ohashi (2019), We utilize the aggregated-level share and product characteristics information for each market and airline and exclude ticket-level information such as advanced purchase due to data limitations. Hence, our demand model assumes that consumers value the aggregated characteristics of an airline's flights in a market, rather than a flight-specific information.

As a formal definition, we consider a consumer's choice set at time t in a market

$m \in \{1, 2, \ldots, M_t\}$ as a set of product $j \in \{0, 1, \ldots, J_{mt}\}$, where $j = 0$ denotes the outside option of not using any flights.

We consider a random coefficient nested-logit (RCNL) model, where the effect of fares and flight frequency are regarded as heterogeneous across consumers. The formal specification of the indirect utility function of consumer i is written as

$$\begin{aligned}
u_{ijmt} &= \alpha_i p_{jmt} + \beta_i f_{jmt} + \mathbf{x}'_{jmt}\gamma + \xi_{jmt} + \varepsilon_{ijmt} && (1)\\
&= \delta_{jmt}\left(p_{jmt}, f_{jmt}, \mathbf{x}_{jmt}, \xi_{jmt}; \alpha, \beta\right) + \mu_{ijmt}\left(p_{jmt}, f_{jmt}, D_i; \Pi\right) + \xi_{igrt} + \varepsilon_{ijmt} && (2)\\
\delta_{jmt} &= \alpha p_{jmt} + \beta f_{jmt}\mathbf{x}'_{jmt}\gamma + \xi_{jmt}\\
\mu_{ijmt} &= [p_{jmt}, x_j]' * \Pi D_i\\
\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} &= \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i + \Sigma \begin{pmatrix} \nu_i^p \\ \nu_i^f \end{pmatrix}, && (3)
\end{aligned}$$

where (α_i, β_i) denotes the consumer-specific coefficients and (α, β) is the average effect of price and frequency. p denotes the average fare, f flight frequency, and $\boldsymbol{x}$ additional exogenous variables, including code-sharing indicator, airline-, market-, or time-specific fixed effects. D_i represents the demographic variables consisting of demeaned income and age, and $\nu_i = (\nu_i^p, \nu_i^f)'$ is the random variation in each consumer's taste. The linear parameters of the RCNL model can be summarized into $\theta_1^d = (\alpha, \beta, \gamma')'$, while the nonlinear parameters of RCNL model can be summarize into $\theta_2^d = (\Pi, \Sigma)$. For the sake of simplicity, we assume that Σ is a diagonal matrix and denote its diagonal elements as (σ^p, σ^f), and D_i and ν_i are independently distributed.

For the unobserved components of this model, ξ represents product-level structural error in utility, which is not captured by the above elements, The correlation between ξ and p and f raises endogeneity issues be addressed in the identification argument later. We assume that $E[\xi_{jmt}]$ and the mean indirect utility from the outside option be 0 as normalization. ε_{ijmt} denotes the idiosyncratic mean-zero error of the consumer-specific deviation from mean utility. A distribution assumption on ε_{ijmt} leads to a corresponding demand system and substitution patterns between products. As long as the Type-I extreme value distribution, we assume that ε_{ijmt} yields a nested-logit structure, where all the products are placed in a single nest whereas the outside goods are separated to another. We use ρ to denote the degree of substitution within the nest. as ρ approaches 0, the nested-logit model collapses to a standard logit model without nests; as ρ approaches 1, then the degree of substitution within the nest is strengthened.

To derive the market share, we assume that consumers choose a single option that gives them a highest utility. Then, integrating over the distribution of ε_{ijmt} returns market shares as

$$s_{jmt} = \int \frac{\exp\left(\delta_{jmt} + \mu_{ijmt}\right)}{1 + \sum_{k=1}^{J_{mt}} \exp\left(\delta_{kmt} + \mu_{ikmt}\right)} dF\left(D_{it}, \nu_{it}\right) \tag{4}$$

Since this market share function depends on the distribution of D_{it} and ν_{it}, we employ the approximation method that uses random draws of D_i and ν_i to compute market shares from the data. Following Gandhi and Nevo (2021), D_{it} is drawn from the National Population Census, and ν_{it} from i.i.d standard normal distribution by modified latin hypercube sampling (MLHS) methods (Hess, Train, and Polak 2006) Assuming $\Pi = \Sigma = 0$ yields the standard nested-logit specification. We also estimate such demand specification and present in Section 5.

The identification problem arises when we estimate the demand parameters $\theta^D = (\theta_1^d, \theta_2^d, \rho)$. We follow the approach of Berry, Levinsohn, and Pakes (1995), which derives the generalized method of moments (GMM) estimator from the population moment condition $E[Z'_{jmt}\xi^*_{jmt}(\theta_0^D)] = \mathbf{0}$. Z is an appropriate vector of instruments, and ξ^* is the product-specific structural error defined as a function of demand parameters. θ_0^D denotes the true demand parameter.

Following Berry, Levinsohn, and Pakes (1995), the GMM estimator for demand-side can be defined as

$$\widehat{\theta}^D = \arg\min_{\theta} \xi^*(\theta)' Z W_d^{-1} Z' \xi^*(\theta) \tag{5}$$

for some positive definite weighting matrix W_d. To obtain an optimal weighting, we employ the two-step GMM estimator.

For consistency, we use several instruments that provide plausible exogenous variation. The first set of instruments is the cost variables that are excluded from the indirect utility function and exhibit no correlation with ξ, which is the typical strategy in the empirical study of demand estimation. We use the average flight characteristics including aircraft size, available number of seats, and maximum takeoff weight. Those variables not only change fares, but also change flight frequency through the maximum number of passengers transported at once. Also, we interact those variables with market-level demographic variables, income and age, to identify the nonlinear parameters. Another set of instruments that affect cost but not demand is composed of fuel expenses. We use a three month lags in the three month moving average of kerosene jet-fuel spot prices to represent the fuel expense for a flight. We also interact this value with the aircraft weight to reflect the approximate amount of loaded fuel. Finally, we use airport charge fees airlines incur at each take-off. The per-flight charges are calculated based on the maximum takeoff weight and noise level at the departure, which we calculate for each airport and aircraft combination, and then take the average in a given year-market-airline combination.

4.2 Supply specification

In this subsection, we build a model of airline market competition to consider the implication of CSA and derive an estimation strategy. We focus on three issues: the vertical structure of the code-shared flights, revenue-sharing rules of CSA, and unilateral ownership of the capital stake between agreement partners. The solution of the comprehensive model reduces to a familiar matrix representation as in **Nevo2000cereal**.

4.2.1 Assumptions in the supply model

We describe salient assumptions in our model of airline market competition. An assumption on individual pricing of code-shared products leads to the vertical structure between CSA partners. Also, we suppose that the CSA works as revenue-sharing rule and capital stake holding induces partial ownership.

We consider a Bertrand competition of differentiated products with a subset of products being code-shared. For the sake of simplicity, we suppress the market and time subscription henceforth. Suppose that the market consists of two airlines, A and B, with each airline operating a single-carrier flight a and b. There exists the other product in this market, the code-shared flight denoted by c, which is operated by airline A.

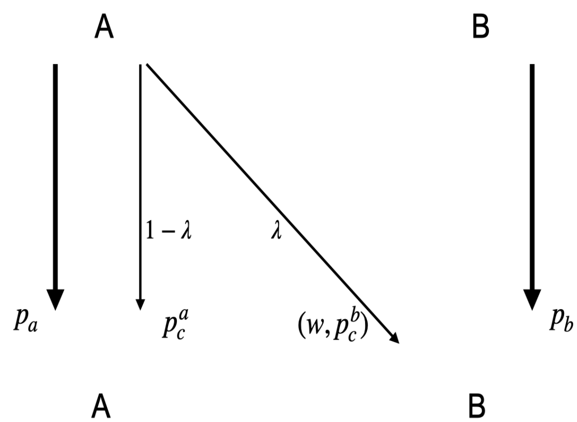
We assume three structures in this particular setting. First, the airlines follow the revenue-sharing rule for the code-shared product. This rule assigns the code-sharing parameter $\lambda \in (0, 1)$ to the airline B, which denotes the partial ownership of this airline to the code-shared product c. Depending on the other assumptions, the airline B either sells λ portion of the code-shared product by themselves or just receives the revenue from the airline A. In the revenue-sharing structure, since both airline have claims over the code-shared product, they are inclined to lessen the competition to save the profit generated from it. Similar assumption on the CSA is found in Shen (2017).

Second, we assume that both partners, A and B, separately sells the tickets of the code-shared product c, which induces a vertical relationship between the two airlines. In the past empirical studies using structural approach, only one airline is supposed to determine the retail price of code-shared products, whether it involves vertical relationship (Gayle 2013) or not (Shen 2017).

On the other hand, under our assumption, the λ fraction of seats of the code-shared product are sold by airline B with its own pricing scheme as often seen in reality. This λ amount of aviation service is *manufactured* by the airline A, and sold to the airline B with a wholesale price w. Then, the airline B sells this seats based on its own pricing, denoted by p_c^b. The remaining $1-\lambda$ fraction of the seats are sold by the airline A with no wholesale price. We denote this retail price as p_c^a. Figure 4 illustrate the structure. We define the average price of the code-shared product c as $p_c = (1-\lambda)p_c^a + \lambda p_c^b$.

Note that without this assumption, it is easier to interpret the code-sharing parameter λ as the rate of simple revenue-sharing rule: the airline A exclusively sells the product a and c, and then through some undisclosed negotiation the λ portion of the revenue from the product c is transferred to the airline B.

Figure 4: The vertical relationship in the market with code-shared product



The vertical relationship between two firms with a code-shared flight is represented. Next to each arrowhead is the wholesale price and retail fare for the product. The purely-operated product a and b, and a part of the code-shared product (with fare p_c^a) are vertically integrated with wholesale prices being zero, so we put to the side of arrows p_j instead of $(0, p_j)$. The remaining part of the code-shared flight c, marketed by airline B, has wholesale price w and retail price p_b^c as attached to the arrow from upstream A to downstream B.

In order to analyse the pricing behaviors, we assume that only the average fares of each flight affect the demand, i.e., the demand is a function of $\mathbf{p} \equiv (p_a, p_b, p_c)'$, independent from p_c^j or identity of the marketing airline for code-shared flights. This assumption allows us to derive the moment conditions from the first-order conditions of airlines' profit maximization problem. Also, it alleviates the data limitation problem: for the code-shared products, we do not have the information of the airlines from which consumers purchased their tickets, so we cannot construct p_c^j, but only p_c for those products. The validity of this assumption is sustained as long as the fare dispersion of the code-shared flight is not too severe compared with the other single-carrier flights; in the first place, many BLP type analyses use the average prices to represent the demand function, and we hope this applies to the present situation.

4.2.2 Solution of the supply model

We solve the supply-side model as a version of Bertrand competition of differentiated products. Although the observable data is limited, we show that a relevant form of price-cost margin can be derived from the airlines' optimal choice, using matrix notation. The quality determination is also considered.

Following the studies of vertical relationship such as Villas-Boas (2007) and Gayle (2013), we first solve the downstream pricing decision, then move to the upstream wholesale price decision. Then, the frequency decision is considered.

Suppose that we have a market with two competing airlines A, B and three products a, b, and c. The first two products are the single-carrier products of airlines A, B, respectively. The product c is code-shared: the airline A operates the aircraft, and airline B sells $\lambda \in (0, 1)$ portion of it to the consumer.

Note that we omit the cross ownership stemming from mutual capital holding for this section. As depicted in O'Brien (2000), such a capital structure can affect the market competition. For the sake of simplicity, we leave the argument related to this point to Appendix B. The intuition of this model is not affected by the exclusion of cross ownership.

We first look at the downstream price decisions. Assuming the vertical structure, airline A decides p_a, p_c^a, f_a, and f_c to maximize the downstream profit. That is, she decides the ticket fares after the wholesale transaction with airline B was conducted. The airline A's problem is written as

$$\max_{p_a, p_c^a, f_a, f_c} \pi_A(\mathbf{p}, \mathbf{f}) = \left[(p_a - mc_a^p) \cdot q_a(\mathbf{p}, \mathbf{f}) - mc_a^f \cdot f_a + (1-\lambda)(p_c^a - mc_c^p) \cdot q_c(\mathbf{p}, \mathbf{f}) - mc_c^f \cdot f_c\right]$$
$$\text{for given } w, p_b, \text{ and } f_b,$$

where mc_p^j and mc_f^j are the per-passenger and per-flight marginal cost of product j, respectively. $q_j(\mathbf{p}, \mathbf{f}) \equiv M \times s_j(\mathbf{p}, \mathbf{f})$ represents the demand function for flight j. apc denotes the average per-flight airport charge.

which means she decides the ticket fares after the wholesale transaction with airline B. We assume that the per-passenger marginal cost of the code-shared flights, mc_c^p, is considered only for the fraction of $(1-\lambda)$, and the rest of the per-passenger cost is assigned to the upstream stage[6]. Note that she incurs full per-flight marginal cost for the code-shared product, mc_c^f, since she actually operates the aircraft.

The first-order conditions (FOC) with respect to p_a and p_c^a are written as

$$
\begin{aligned}
0 &= q_a(\mathbf{p},\mathbf{f}) + \frac{\partial q_a}{\partial p_a}(\mathbf{p},\mathbf{f})(p_a - mc_a^p) + \frac{\partial q_c}{\partial p_a}(\mathbf{p},\mathbf{f}) \cdot (1-\lambda)(p_c^a - mc_c^p) && (6)\\
0 &= \frac{\partial q_a}{\partial p_c^a}(\mathbf{p},\mathbf{f})(p_a - mc_a^p) + \frac{\partial q_c}{\partial p_c^a}(\mathbf{p},\mathbf{f}) \cdot (1-\lambda)(p_c^a - mc_c^p) + (1-\lambda) q_c(\mathbf{p},\mathbf{f}) \\
\Leftrightarrow 0 &= \frac{\partial q_a}{\partial p_c}(\mathbf{p},\mathbf{f})(p_a - mc_a^p) + \frac{\partial q_c}{\partial p_c}(\mathbf{p},\mathbf{f}) \cdot (1-\lambda)(p_c^a - mc_c^p) + q_c(\mathbf{p},\mathbf{f}) && (7)
\end{aligned}
$$

where we utilize the assumption of $p_c = (1-\lambda)p_c^a + \lambda p_c^b$, which implies $\frac{\partial q_i}{\partial p_c^a} = (1-\lambda)\frac{\partial q_i}{\partial p_c}$. Recall that the airline B's problem is written as

$$
\max_{p_b, p_c^b, f_b} \pi_B = \Big[(p_b - mc_b^p) \cdot q_b(\mathbf{p},\mathbf{f}) - mc_b^f \cdot f_b + (p_c^b - w) \cdot \lambda q_c(\mathbf{p},\mathbf{f}) + \kappa \pi_A(\mathbf{p},\mathbf{f})\Big]
$$
$$
\text{for given } p_a, p_c^a, w, f_a, f_c.
$$

$$
\max_{p_b, p_c^b, f_b} \pi_B = \Big[(p_b - mc_b^p) \cdot q_b(\mathbf{p},\mathbf{f}) - mc_b^f \cdot f_b + (p_c^b - w) \cdot \lambda q_c(\mathbf{p},\mathbf{f})\Big]
$$
$$
\text{for given } p_a, p_c^a, w, f_a, f_c.
$$

Putting aside the flight frequency, FOCs with respect to p_b and p_c^b are as follows.

$$
\begin{aligned}
0 &= q_b(\mathbf{p},\mathbf{f}) + \frac{\partial q_b}{\partial p_b}(\mathbf{p},\mathbf{f})(p_b - mc_b^p) + \lambda \frac{\partial q_c}{\partial p_b}(\mathbf{p},\mathbf{f})(p_c^b - w) && (8)\\
0 &= \frac{\partial q_b}{\partial p_c}(\mathbf{p},\mathbf{f})(p_b - mc_b^p) + \left(\lambda \frac{\partial q_c}{\partial p_c}(\mathbf{p},\mathbf{f})(p_c^b - w) + q_c(\mathbf{p},\mathbf{f})\right) && (9)
\end{aligned}
$$

where Eq. (8) is for p_b and Eq. (9) for p_c^b. We use similar technique to derive (9) to (7): $\frac{\partial q_i}{\partial p_c^b} = \lambda \frac{\partial q_i}{\partial p_c}$.

6. This assumption is innocuous because we can add up the downstream marginal cost and upstream marginal cost eventually.

The interpretation of (8) is straightforward: B behaves as if the product c is partially owned by her since she sells λ part of code-shared product. Similar interpretation holds for Eq. (9), but we need slight modification on the second term. Since the fare offered by the airline B, p_c^b, partially change the average fare of code-share product c, the marginal change in its demand responding to an increase in p_c^b is discounted by λ.

Collecting the FOCs with respect to prices, (6), (8), (7), and (9) yields the following matrix representation.

$$\begin{pmatrix} q_a(\mathbf{p},\mathbf{f}) \\ q_b(\mathbf{p},\mathbf{f}) \\ q_c(\mathbf{p},\mathbf{f}) \\ q_c(\mathbf{p},\mathbf{f}) \end{pmatrix} = \Omega^p(\lambda) \otimes \Delta^p \begin{pmatrix} p_a - mc_{pa} \\ p_b - mc_b^p \\ p_c^a - mc_c^p \\ p_c^b - w \end{pmatrix} \tag{10}$$

$$\text{where} \quad \Omega^p(\lambda) \equiv \begin{pmatrix} 1 & 0 & 1-\lambda & 0 \\ 0 & 1 & 0 & \lambda \\ \frac{1}{1-\lambda} & 0 & 1 & 0 \\ 0 & \frac{1}{\lambda} & 0 & 1 \end{pmatrix}$$

$$\Delta^p = \begin{pmatrix} \nabla_{p_a}\widetilde{\mathbf{q}}(\mathbf{p},\mathbf{f})^T \\ \nabla_{p_b}\widetilde{\mathbf{q}}(\mathbf{p},\mathbf{f})^T \\ \nabla_{p_c^a}\widetilde{\mathbf{q}}(\mathbf{p},\mathbf{f})^T \\ \nabla_{p_c^b}\widetilde{\mathbf{q}}(\mathbf{p},\mathbf{f})^T \end{pmatrix} \tag{11}$$

$$\widetilde{\mathbf{q}}(\mathbf{p},\mathbf{f}) = \begin{pmatrix} q_a(\mathbf{p},\mathbf{f}) \\ q_b(\mathbf{p},\mathbf{f}) \\ q_c(\mathbf{p},\mathbf{f}) \\ q_c(\mathbf{p},\mathbf{f}) \end{pmatrix} \tag{12}$$

where Ω^p is the ownership matrix in this model. The third row and the forth row are normalized so that the diagonal elements take the value 1. Δ^p is the price derivatives of the demand function for all four prices, p_a, p_b, p_c^a, and p_c^b in this market.

Hence, we can obtain the matrix representation of price-cost margins of four prices as

$$\begin{pmatrix} p_a - mc_a^p \\ p_b - mc_b^p \\ p_c^a - mc_c^p \\ p_c^b - w \end{pmatrix} = -\left(\Omega^p(\lambda) \otimes \Delta^p\right)^{-1} \widetilde{\mathbf{q}} \tag{13}$$

Since we observe aggregated price of the code-shared product p_c, instead of p_c^a and p_c^b, we need to manipulate (13) to obtain the price-cost margin for p_c. Multiplying a following matrix T yields the desired result.

$$
\begin{aligned}
\begin{pmatrix} p_a - mc_a^p \\ p_b - mc_b^p \\ p_c - mc_c^p - \lambda(w - mc_c^p) \end{pmatrix} &= T \begin{pmatrix} p_a - mc_a^p \\ p_b - mc_b^p \\ p_c^a - mc_c^p \\ p_c^b - w \end{pmatrix} \\
&= -T \left(\Omega^p(\lambda) \otimes \Delta^p\right)^{-1} \tilde{\mathbf{q}} \\
\text{where} \quad T &= \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1-\lambda & \lambda \end{pmatrix}
\end{aligned}
\tag{14}
$$

That is, T is a operation by which we take a weighted sum of the third row and the forth row and eliminate the forth row. By extracting the first to third rows of (14), we obtain the downstream markup terms, which still contains the upstream markup $\lambda(w - mc_c^p)$.

To derive the equilibrium price for code-shared flights p_c, we solve the upstream problem. The upstream airline A decides the wholesale price of the code-shared seats vis-a-vis the marketing airline B, which is formulated as

$$
\begin{aligned}
&\max_w \lambda(w - mc_c^p) q_c(\mathbf{p}, \mathbf{f}) \\
&\text{subject to } p_c^b = p_c^b(w)
\end{aligned}
\tag{15}
$$

where $p_c(w)$ is derived from the first-order condition of the airline B's problem with respect to the p_c^b. A's profit maximization problem is subject to the upstream pricing equation for the code-shared product. This is because the airline A knows that λ fraction of the code-shared product is sold by her partner and the ticket price is dependent on the wholesale price, as well as her own decision at the downstream market. From the first-order condition with respect to the wholesale price, we can derive the optimal wholesale price as

$$
w^* = mc_c^p + \lambda^{-1} \left(-\frac{\partial q_c}{\partial w}\right)^{-1} q_c(\mathbf{p}, \mathbf{f})
$$

where $\partial q_j/\partial w$ is the derivative of product j with respect to wholesale price w. In Appendix B.2, we discuss how to compute this derivative and its dependence on the code-sharing parameter λ. Substituting this to the pricing equation Eq. (14), we obtain the equilibrium price-cost margins

$$\mathbf{p} - \mathbf{mc^p} = -T\left(\Omega^p(\lambda) \otimes \Delta^p\right)^{-1} \tilde{\mathbf{q}} + \begin{pmatrix} 0 \\ 0 \\ -\left(\frac{\partial q_c}{\partial w}\right) q_c(\mathbf{p}, \mathbf{f}) \end{pmatrix} \tag{16}$$

$$\text{where} \quad \mathbf{p} = \begin{pmatrix} p_a \\ p_b \\ p_c \end{pmatrix}, \quad \mathbf{mc^p} = \begin{pmatrix} mc_a^p \\ mc_b^p \\ mc_c^p \end{pmatrix}$$

The price-cost margins consist of the downstream and upstream markup terms. The downstream markup is represented by the first term of the right hand side of Eq (16). The upstream markup, only relevant for the code-shared product, is represented by the second term, which depends on the wholesale price derivative.

Utilizing those markup equations, We can write down the first-order conditions for flight frequencies f_a, f_b, and f_c as

$$mc_a^f = \frac{\partial}{\partial f_a} q_a(p_a - mc_a^p) + (1-\lambda)\frac{\partial}{\partial f_a} q_c(p_c^a - mc_c^p) \tag{17}$$

$$mc_b^f = \frac{\partial}{\partial f_b} q_b(p_b - mc_b^p) + \lambda\frac{\partial}{\partial f_b} q_c(p_c^b - w) \tag{18}$$

$$mc_c^f = \frac{\partial}{\partial f_c} q_a(p_a - mc_a^p) + (1-\lambda)\frac{\partial}{\partial f_c} q_c(\mathbf{p}, \mathbf{f}) \tag{19}$$

which allows us to estimate the per-flight marginal cost function.

The matrix representation for the quality decision can be derived in a similar way.

$$
\mathbf{mc^f} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \left[\Omega^f(\lambda) \times \Delta^f \right] \begin{pmatrix} p_a - mc_a^p \\ p_b - mc_b^b \\ p_c^a - mc_c^p \\ p_c^b - w \end{pmatrix} \tag{20}
$$

$$
\text{where} \quad \Omega^f(\lambda) = \begin{pmatrix} 1 & 0 & 1-\lambda & 0 \\ 0 & 1 & 0 & \lambda \\ \frac{1}{1-\lambda} & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}
$$

A slight modification of the ownership matrix, from Ω^p to Ω^f, is needed because of the dimension of quality variable $\mathbf{f}$.

We can also build different models by modifying the ownership matrix or the dimension of variables. For example, we can consider a extreme case of anti-competitive effect of CSA: the airlines engaging in CSA behave collusively. In that case, we have a following matrix representation.

$$
\mathbf{p} - \mathbf{mc^p} = -\left(\Omega^p_{collusion} \otimes \Delta^p\right)^{-1} \mathbf{q}
$$

$$
\text{where} \quad \Omega^p_{collusion} = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix}
$$

We employ such alternative specifications to verify the appropriateness of our model assumption in Section 5 and to explore the effect of CSA in Section 6.

4.2.3 supply estimation

We describe the estimation approach of the supply-side parameters based on GMM argument.

In order to estimate the marginal cost functions, we specify the per-passenger and per-flight marginal costs as

$$
\log\left(mc^p_{jmt}\right) = \mathbf{w}'_{jmt}\gamma^p + \eta^p_{jmt} \tag{21}
$$

$$
\log\left(mc^f_{jmt} + apc_{jmt}\right) = \mathbf{w}'_{jmt}\gamma^f + \eta^f_{jmt} \tag{22}
$$

$$
\tag{23}
$$

where $\mathbf{w}^x_{jmt}$ denotes the observed product characteristics that affect marginal costs, including fuel price, average aircraft size, engine compassion ratio, and fixed effects. η^x_{jmt} denotes the structural error that is not captured by $\mathbf{w}^x_{jmt}$. apc_{jmt} denotes the per-flight airport charge. We assume that those observed characteristics are independent from the structural error.

Taking the demand estimation result as given, we estimate the supply side of the model. Based on the discussion in the previous section, the supply-side parameters to be estimated are summarized to the vector $\theta^s = (\gamma^p, \gamma^f, \lambda)^\top$, and we define $\eta^*(\theta^s; \theta^d)$ to represent the stacked structural errors as a function of the given parameter values. Specifically, η^* consists of η^{p*} and η^{f*}, where η^{p*} comes from markup term equations Eq. (16), and η^{f*} from Eq. (20). Then, we can define the GMM estimator using appropriate instruments Z^s

$$\widehat{\theta}^s = \arg\max_{\theta} \eta^*(\theta; \widehat{\theta}^d) Z W^s Z^\top \eta^*(\widehat{\theta}; \theta^d) \tag{24}$$

To obtain a consistent estimator, we have to deal with the endogeneity problem arising from the markup terms, which contain unobserved cost shocks through demand functions. Since our model implies that the price-cost margins of some products contains other products' price-cost margins, it is inappropriate to employ cost shifters of others, $\mathbf{w}^x_{-j}$ as IV. Hence, we use two types of demand shifters that do not enter in the supply-side model as instruments, following the argument of Berry and Haile (2014). The first is the demand shifter included in the demand system linearly, the peak time ratio of each product. As we discuss in Section 5, it impacts the demand in a positive way by providing consumers with a convenient schedule. The second is the non-linear part of demand shifters, that is, changes in the distribution of demographics across markets. For example, demand and markups for products may be higher in markets with aging population, who prefers comfortable transportation; the marginal costs, on the other hand, is unlikely to be affected by demographics.

5 Results

5.1 Demand side

The table 3 shows the results of demand estimation. Each column corresponds to different specifications. Columns (1) corresponds to the nested-logit specifications, where the distributions of random coefficients are assumed to be degenerated. From

(2) to (4), we show the estimation results of RCNL specifications: (2) is that the basic specification, whereas (3) and (4) extends it to include codeshare-related variables in consumer tastes. The column (4) shows the result of RCNL model with market-, airline-, and year-fixed effects.

Many estimates exhibit statistically significant values with appropriate direction in their signs. All estimated fare coefficient is statistically and economically significant. Specification (1) yields the average own-price elasticity of -1.97, which is in line with the past finding in both Japanese domestic airline (Doi and Ohashi 2019) and U.S. airline market (Gayle 2013). The RCNL gives similar own price elasticity from 1.93 to -2.51.

The RCNL specification has positive estimates for flight frequency. In the nested-logit specifications, we add the square term of the flight frequency to capture its impact on consumer taste as flexible as possible. Since the flight frequency is endogenized in the supply model, we also calculate the own-frequency elasticity to see the relative importance of frequency for consumers. The nested-logit specification yields average values around 0.57, whereas the RCNL model gives around 0.821. Those values implies that consumers evaluate frequency and will respond to the change in frequency elastically.

We also try to consider demand-side effect of codeshare in several ways. First, the estimated coefficient of codeshare dummy is negative, and significant in some specifications. The negative signs imply that code-shared products are perceived as low-quality products by consumers, as Ito and Lee (2007) suggest. This argument is based on the fact that consumers cannot use first-class seats or only receive limited in-flight services compared to those of FSCs.

In the present data set, some consumers of code-shared flights purchase their tickets from the operating airline's website. For those consumers, since the aviation service is indifferent whether they use a code-shared or single-carrier flight, the quality of code-shared products should be reckoned same as the the single-carrier. The above argument of inferior product quality only applies to the consumers from marketing airlines, and the negative estimates are supposed to be driven by these consumers. To verify this conjecture, in column (3) we include the interaction of the codeshare dummy and the regulation dummy that indicates whether the observation time is after the regulatory change in the ceiling of code-sharing level. Since the regulatory ceiling increased from 25% to 50% in 2013, the ratio of consumers from marketing airlines are likely to increase; that means the code-shared flights are more disliked on average, resulting in the negative coefficient of this interaction dummy. Although not statistically significant, the coefficient of the interaction shows negative sign. This result supports the Ito and Lee (2007)'s hypothesis.

Along with the negative side, we also consider the positive effect of codeshare in demand side in the column (4). First, we include the marketing airline dummy, capturing the benefit of expanding the consumer base. By codeshare, the product can reach consumers in both airlines' consumer base. The dummy tries to represent this effect. Also, we add flight frequency of the marketing airline for a code-shared product. The higher the flight frequency of the marketing airline's product is, the more likely consumers of the marketing airline are to find their convenient departure time. Both coefficients are expected to be positive, which is consistent in the result presented in the columns (4).

The nest parameter, ρ, is estimated around 0.3, which is again consistent with the past findings as in Doi and Ohashi (2019). Relatively low value of this estimate indicates that substitution between air travel and other transportation methods is somewhat strong. It is known that the high-speed railway (HSR) is well-developed in Japan and has been a prominent competitor in a certain transportation markets. While we try to consider the presence of HSR by incorporating the market-fixed effect, the result implies the relevance of different modes of transportation as substitutes.

The demand specification also includes several variables reflecting the airline-market characteristics. The dummy variable of code-shared flight has a significantly negative estimate, implying that consumers regard code-shared products as low-quality products by consumers as Ito and Lee (2007) suggest. The dummy of slot control airports, which takes value one if either of the endpoints airport is slot-controlled by regulators due to congestion, does not exhibit significant estimate. This is possible because the market specific effect absorbs the most of such congestion or low-convenience disutility from this variable. We also include the variable that indicates the ratio of flights which departs during the peak time. As many flights are departing in peak time, that route is expected to become more convenient, which is consistent with the significantly positive estimates.

Henceforth, we use the specification (2) as the demand function.

Note that the overidentification test is not rejected at 5% significance level for all the four specifications, implying that we can not reject the null hypothesis of the valid moment conditions.

5.2 Supply side

This subsection provides the estimation results on supply-side model with marginal cost function and profit sharing rule with code-sharing agreements. We also present Rivers-Vuong test of non-nested models in order to compare the estimated model with the model under different assumptions, such as CSA-cartel hypothesis.

Table 4 shows the estimated supply-side model of code-sharing parameters and

Table 3: Results of demand estimation

Model:	Nested-Logit	RCNL		
	(1)	(2)	(3)	(4)
fare (hundreds, JPY)	-0.0127*	-0.0457***	-0.0843**	-0.0771**
	(0.0017)	(0.0021)	(0.0041)	(0.0391)
flight frequency	-0.1142	0.1479	0.302	0.3249
	(0.0809)	(0.2001)	(0.2261)	(0.3444)
(flight frequency)^2	0.0160***			
	(0.0056)			
code sharing dummy	-0.3291***	-0.1371	-0.1556	-0.9199***
	(0.0998)	(0.3187)	(0.2772)	(0.2376)
code sharing × regulation			-0.1096	
			(0.3492)	
marketing carrier dummy				0.8811***
				(0.2353)
flight frequency (CSA partner)				0.0110
				(0.0543)
slot control dummy	0.0236	-0.1603***	-1.494***	-1.339***
	(0.1418)	(0.1364)	(0.4218)	(0.3368)
peak time ratio	0.076**	0.425**	0.2587	0.3382*
	(0.0373)	(0.2153)	(0.2812)	(0.2112)
ρ	0.3465***	0.3133**	0.2891***	0.3232***
	(0.1615)	(0.1684)	(0.1442)	(0.1449)
σ^p		-0.0083**		0.0187**
		(0.0033)		(0.0083)
σ^f		0.017	0.1353	-0.2343
		(0.245)	(0.2897)	(0.4057)
Fixed-effects				
OD	Yes	Yes	Yes	Yes
Airline	Yes	Yes	Yes	Yes
First-stage F statistics	24.787			
GMM objective function value	0.005	0.006	0.006	0.006
Number of Observations	2,460	2,460	2,460	2,460

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The numbers in parentheses are standard errors that are clustered by markets. The level of prices are deflated in constant 2011 JPY, when exchange rate of U.S. dollar to JPY was 86.7. We omit the estimates of Π for the sake of simplicity.

marginal cost functions. We estimate two models under different assumptions. The first model, presented in the column A is the model embodying all the assumptions we explain in Section 4.2: CSA induces vertical relationship and revenue-sharing between airlines, and airlines may have some capital stake of other airlines, which elicits the change in airlines' incentive.

The first panel shows the estimates of CSA parameters λ. To reduce the dimension of parameters, we split the sampling period into two folds based on the regulation. The first period is 2011, before the regulatory maximum of λ changes from .25 to .5 in 2012. We denote it by $\lambda_{\sim 2012}$. The other period is 2013, 2015, and 2017, which is denoted by $\lambda_{2012\sim}$.

In both periods, estimates are statistically significant at 5% level, and consistent with the regulatory ceiling. $\lambda_{\sim 2012}$ is substantially lower than the supposed ceiling value, while it is compatible with the study of U.S. domestic CSA (Shen 2017). Although he focuses on a particular period of 2004, our result suggests that the practice of CSA significantly changes as the regulation alternates.

The estimates of marginal cost functions implies the existence of economy of scale, which is consistent with other findings. As aircraft size increases, the per-passenger cost significantly and substantially decreases. On the other hand, the increase in aircraft size raises per-flight cost, possibly because of higher operational costs associated with larger aircrafts. The interaction of fuel price and aircraft size does not exhibit significant estimates. This can be attributed to the high-dimensional fixed costs included in the cost functions.

The coefficient on the codeshare dummy captures the cost efficiency associated with codeshare, which exhibits statistically and economically significant value of -0.2. That is equivalent to around 15% decrease in per-passenger marginal cost for a product with average level marginal cost of 145 per passenger. The main source of cost efficiency can be considered as the effective coordination of marketing system, as pointed in Chua, Kew, and Jong (2005). The cost efficiency does not appear in the per-flight cost function, supporting our interpretation and suggesting that CSA does not affect the operational cost of aircrafts.

The other column, B, presents the results of a different model from the full-assumption model A: in model B, we assume that the cross ownership of capital stake does not affect the airlines' incentive. That is, even if an airline XXX is acquiring certain amounts of capital stake of another airline YYY, the decision of both airlines does not change[7]. Although two models has a common form of CSA and CSA paramters λ, airlines' decision

7. In model A, such an assumption allows ANA to consider the revenue flow via capital stake from ADO, for example. That leads to the higher markup charged by ANA. For the detail, see Appendix B

may differ because of the capital stake.

The results on the CSA parameters exhibits a distinction between the two models. In both periods, they are estimated 6-15% higher in the model B. Hence, we can say that CSA and capital relationship are complements in the following sense: to justify the same amount of markups, airlines without capital relationship must enhance the degree of CSA. On the other hand, the estimates of cost parameters are indifferent between the two models, which indicates the importance of considering the relationship between CSA and capital stakes.

A possible implication is that CSA can work as a substitute for capital relationship for airlines to cooperate. The regulation poses restrictions on the maximum amount of capital stake competitors can obtain. Such regulation, however, can be avoided to a certain degree by forming CSA and enhance it. That leads us to the speculation of anti-competitive effect CSA might have.

Note that the overidentification test fails to reject the null hypothesis of the valid moment conditions in both models, supporting the appropriateness of instruments.

To assess the appropriateness of the supply-side assumptions, we employ the statistical test of non-nested models. Rivers and Vuong (2002) propose a testing framework for a broad class of objective functions including GMM . In the present setting, we examine two models that are non-nested, such as the model with all assumptions and the model of CSA-cartel. The null hypothesis is that both specifications are equally incorrect. Using the GMM objective function $Q_A(\theta^A)$ and $Q_B(\theta^B)$, the Rivers-Vuong test statistics is given as

$$T = \frac{\sqrt{n}\left(Q_A(\theta^A) - Q_B(\theta^B)\right)}{\sigma},$$

where σ is the standard error of the difference between the objective functions. Rivers and Vuong (2002) show that T asymptotically follows standard normal distribution; the null hypothesis is rejected in favor of model A if T is smaller than $-z_{1-\alpha/2}$, and rejected in favor of model B if T is greater than $z_{1-\alpha/2}$, where α is significance level and z_a is the a-percent percentile of the standard normal distribution.

For implementation, we follow the testing procedure proposed by Backus, Conlon, and Sinkinson (2021) to use bootstrapped samples for estimating the standard error of difference between objective functions. We draw 100 bootstrap samples clustered at the market by year level.

We report the test result in Table 5. We consider three models against the model of full CSA assumptions, denoted by A. The first two is about the role of capital stake

Table 4: Results of supply estimation

	A: full assumptions		B: without capital stake effect	
	$\ln(mc^p)$	$\ln\left(mc^f\right)$	$\ln(mc^p)$	$\ln\left(mc^f\right)$
CSA parameters				
$\lambda_{\sim 2012}$	0.086^{***}		0.105^{***}	
	(0.042)		(0.049)	
$\lambda_{2012\sim}$	0.398^{***}		0.423^{***}	
	(0.015)		(0.017)	
cost parameters				
aircraft size	-0.004^{**}	0.023^{**}	-0.003^{**}	0.021^{***}
	(0.002)	(0.008)	(0.001)	(0.007)
fuel price × aircraft size	0.003	0.33	-0.001	0.021
	(0.021)	(0.122)	(0.015)	(0.273)
codeshare dummy	-0.203^{***}	-0.03	-0.226^{***}	-0.021
	(0.096)	(0.232)	(0.087)	(0.281)
Fixed-effects				
OD-Year	Yes		Yes	
Airline	Yes		Yes	
Observations	2,460		2,460	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The numbers in parentheses are standard errors that are clustered by markets. The levels of prices and fees are deflated in constant 2011 JPY, when exchange rate of U.S dollar to JPY was 86.7.

and CSA. As we show in Table 4, the code-sharing parameters can vary depending on the assumption of capital stake, which suggests a certain interaction between the capital stake relationship and CSA. Hence, we try to examine the model that best describes the data in relation to the capital stake assumption. In particular, we consider two extreme models. First is the model B in the previous paragraphs, i.e., the model where capital stake does not have any effect on the airlines' decision making. On the other hand, we posit a model denoted by *CSA-cartel*, which assumes that the airlines holding CSA and capital relationship cooperate as if they are horizontally merged.

The RV test implies that both models of are not as fitting to data as the full-assumption model. The data does not support neither hypothesis that capital stake is irrelevant, nor the one that the capital stake and CSA are used for making a cartel.

We also confirm the validity of our assumptions in terms of competition form and CSA, in line with Gayle (2013): we study whether our assumption of vertical relationship does explain data well compared with the model without any vertical relationship. The result again supports the model of full assumptions, including vertical relationship, which is also consistent with the result of Gayle (2013).

Hence, we rely on the model of CSA to carry out the following analysis of markups and counterfactual simulations.

Table 5: Results of Rivers-Vuong test

	A: Full CSA assumptions
Capital stake and CSA	
B: no capital stake	5.22***
	(0.002)
D: CSA-cartel	4.69***
	(0.009)
CSA and competition	
C: no vertical relationship	2.64**
	(0.003)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The numbers in the parentheses are standard errors, which are computed from the 100 draws of Bootstrap samples. Bootstrap samples are clustered at each market by year.

Using the estimated model, we try to gain insights into the relative competitiveness and profitability of code-shared products. In Table 6, we report the median elasticity, per-passenger and -flight marginal costs, and price-cost margins for non code-shared and code-shared products, recovered from the model. The first two rows show the own-elasticity: code-shared products exhibit higher own-price elasticity, implying that the consumers are more price-sensitive to those products. This is consistent with the low observed fares of code-shared products in the data, as in findings on U.S. domestic CSA (Shen 2017), On the other hand, the lower own-frequency elasticities for code-shared product imply that product quality of those products is less important in consumer's taste.

The second two rows report the marginal costs estimates. The per-passenger costs decreases by around 15% on average by codeshare due to the cost efficiency. Although our estimates does not show significant change in per-flight cost by codeshare, the per-flight costs differs substantially: the median per-flight cost of purely-marketed products is around three times larger than that of code-shared products. This large difference can be attributed to the difference in the sizes of aircrafts. The weight of aircrafts used in the code-shared flights are 10 to 20% smaller on average, which reduces per-flight operational costs.

Finally, the last two rows show the price-cost margins. In the first row, we calculate the price-cost margins using the per-passenger cost, but ignoring the per-flight marginal cost, which corresponds to Lerner index in standard specifications. Since the model entails the further cost structure, in the second one, we take into account the per-flight marginal cost to calculate the additional per-passenger cost, dividing the per-flight marginal cost by the number of passengers. The price-cost margins for non-codeshare products are 0.32 and 0.36, similar to the results of other airline studies including Gayle (2013), Shen (2017), and Doi and Ohashi (2019). In both measures, despite of the low cost structure, the price-cost margins of code-shared products are around 20% smaller than those of non code-shared products. A possible interpretation of the poor profitability is that the high own-price and low own-frequency elasticities are significantly affecting the demand for code-shared products.

6 Counterfactual Simulation

In this section, we conduct a counterfactual simulation to quantify the effect of CSA on market outcomes and social welfare. The result shows that introducing CSA raises fares significantly and decreases social welfare, even if the product qualities are endogenously determined. We further explore the implication for competition policy, in comparison with the regulation of mutual capital ownership between airlines: the simulation suggests that airlines could bypass the upper bound of capital holding via forming CSA.

Table 6: Elasticities, marginal costs, and price-cost margins

	Non codeshare	Codeshare
Elasticities		
Own-price elasticity	-2.12	-2.43
Own-frequency elasticity	0.89	0.66
Marginal costs		
Per-passenger (1,000 JPY)	15.25	12.02
Per-flight (million JPY)	97.47	27.05
Price-cost margins		
Per-passenger cost only	0.36	0.30
Including per-flight cost	0.32	0.25

Note: The sampling period consists of 2011, 2013, 2015, 2017. The markup term is calculated from estimated per-passenger and per-flight marginal cost with average number of passengers for each flight, and averaged within the segment.

To evaluate the effect of CSA introduced in the domestic market, we take into acount both the partial ownership and vertical relationship we describe in Section 4. In short, The vertical relationship affects the pricing of the code-shared products via wholesale pricing (double marginalization); also, the partial ownership of the code-shared product in the downstream market can dampens the market competition. Hence, we consider a counterfactual simulation where the code-shared product is vertically integrated and solely owned by the operating airline, and the supply-side model reduces to a standard, horizontal competition of differentiated products among multi-product airlines.

For example, consider the simple market we describe in Section 4.2, which consists of airlines A and B with product a, b, and c. Since the competition now becomes horizontal, we can write the price/frequency first-order conditions using a ownership matrix, Ω, defined as

$$(\mathbf{p}_{mt} - \mathbf{mc}^p_{mt}) = -\left(\widetilde{\Omega}_{mt} \otimes \Delta^p_{mt}(\mathbf{p}_{mt}, \mathbf{f}_{mt})\right)^{-1} \mathbf{s}_{mt} \tag{25}$$

$$\mathbf{mc}^f_{mt} = \widetilde{\Omega}_{mt} \otimes \cdot\Delta^f_{mt}(\mathbf{p}_{mt}, \mathbf{f}_{mt})\left(\mathbf{p}_{mt} - \mathbf{mc}^p_{mt}\right) \tag{26}$$

$$\widetilde{\Omega}_m t = \begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{pmatrix}. \tag{27}$$

ignoring the cross ownership stemming from capital structure.

In this scenario, a code-sharing agreement is considered as an ex-post profit sharing that takes place after the competition. $100 \times \lambda$-percentage of profits from the code-shared product c is distributed to the airline B, while B does not care that revenue flow when making a decision. This is a assumption necessary to quantify the effect of CSA employed in the markets. The first-order Eq. (25) and Eq. (26) and ownership matrix Eq. (27) allows me to compute a new equilibrium fares and flight frequency.

Note that in this scenario, we assume that the market structure and CSA are exogenously given. The identities of competitors are the same as before, and all products, including the code-shared one, have strictly positive flight frequency. Since this can be restrictive and inappropriate in some cases, We choose 20 markets which has more than (i) three competitors and (ii) average-level market size. It turns out the new equilibrium does not predict non-positive values of flight frequency in the selected markets, implying the assumption is not binding. We also assume market sizes are exogenously determined regardless of airlines actions.

To quantify the change in social welfare caused by the CSA, we follow the methods of Small and Rosen (1981) to calculate the expected consumer welfare, as in Gayle (2013). Formally, the expected consumer surplus measured by compensating variation for consumer i in a market m at time t is given by

$$CS_{imt} = \frac{1}{\alpha_i} \ln \left[\sum_{j=0}^{J_{mt}} e^{V_{ijmt}} \right], \tag{28}$$

where α_i is the random coefficient on price and $V_{ijmt} = \delta_{jmt} + \mu_{ijmt}$ from Eq. (1). Let CS^*_{imt} denote the consumer surplus under the counterfactual scenario and CS_{imt} the consumer surplus recovered from the estimates and specification in Section 4.2. The change in consumer surplus for i due to the introduction of CSA is defined as $\Delta CS_{imt} = CS^*_{imt} - CS_{imt}$. Using the drawn values of D_i and ν_i and the market size, we can compute the changes in expected consumer surplus for a market.

To assess the relevance of airline's quality choice to the market outcomes and implication of CSA, we calculate two equilibria. One equilibrium treats the flight frequency as exogenous, whereas the other considers the flight frequency determined endogenously at equilibrium. Table 7 shows the average change in market fare, flight frequency, passenger volumes, and welfare in the markets we pick up. With only fares endogenously chosen by airlines, the CSA raises market fare by 15.1% on average and lowers the consumer surplus by 6.4%. The producer surplus increases by 8.1%, while the total surplus decreases 3.7%. That suggests the cost efficiency of codeshare is limited compared to the welfare loss caused by CSA.

In the right column of Table 7, we show the results when endogenizing the flight frequency. The degree of fare increase becomes larger by four percentage point and the welfare loss was relieved. This can be attributed to the increase in flight frequency, by 6.5%. Since the average frequency across markets we study is around six, the increase is equivalent to an additional flight in a market of three competitors on average. In both specifications, producer surplus increases due to large price increase. Since the decrease in the consumer surplus is significant, the total surplus would decrease by three percent once we introduce CSA.

It can be seen that the incorporating endogenous frequency choice alters the welfare implication of CSA, but the overall pattern is robust to the treatment of product quality in our setting.

Table 7: The effect of CSA compared with competitive market

	Exogenous flight frequency	Endogenous flight frequency
Δ Fare (%)	15.1	18.2
Δ flight frequency (%)	–	6.5
Δ Passenger volume (%)	-7.8	-12.8
Δ Consumer surplus (%)	-5.7	-6.4
Δ Producer surplus (%)	8.1	9.5
Δ Total surplus (%)	-3.7	-3.2

Note: Effects are measured as the difference of outcomes between an equilibrium without CSA and an equilibrium under CSA. The left column uses a CSA-equilibrium with frequency exogenous, while the right uses a CSA-equilibrium with frequency endogenous.

To further investigate the impact of CSA on market competition, we try to decompose its effect in two directions. First, we consider the change in market structure caused by CSA. As we discuss, CSA induces (i) partial ownership in downstream market and (ii) vertical relationship of code-shared products. We consider an equilibrium where CSA entails partial ownership, but does not bring vertical relationship. By observing the effect of such a *horizontal CSA*, we can uncover the relevance of each components of CSA.

The first panel of Table 8 shows the result. The left column corresponds to the change caused by a hypothetical *horizontal CSA*. The right corresponds to CSA with both partial ownership and vertical relationship, which is the same result as the Table 7. Compared to the full specification, the increase in fare and flight frequency under horizontal CSA is modest, by 7.3% and 2.0%, respectively. Hence the degree of loss in consumer welfare is also smaller. On the other hand, between the two specifications, the increase in producer surplus is not significantly different, which is mainly due to the price-sensitive demand functions. Although the horizontal structure makes the market competition less severe, adding the vertical relationship particularly raise market fares, but it does not contribute to overall airlines' profit.

Next, we also try to address the question of which airline is affected and benefited by CSA. To do so, using the equilibrium calculated in 7, we decompose the CSA effect into two parts: those of airlines involving in CSA and those of not. As is shown in the second panel of Table 8, the simulation yields a substantial increase in fares posted by CSA airlines, over 20%, which in turn lowers passenger volumes to a large degree of 19%. By contrast, for non-CSA airlines, the fare increase is relatively modest, and, surprisingly, the passenger volume increases slightly. That is partly because of the business stealing effect from raised fares of the CSA airlines, as well as the nesting structure of the demand. As a result, the Non-CSA airlines enjoy more profit increase, by 15%, than CSA airlines.

Table 8: The decomposition of the CSA effect

	Structure level	
	CSA (horizontal)	CSA (horizontal + verical)
Δ Fare (%)	7.3	18.2
Δ flight frequency (%)	2.0	6.5
Δ Passenger volume (%)	-5.1	-12.8
Δ Consumer surplus (%)	-2.2	-6.4
Δ Producer surplus (%)	8.4	9.5
Δ Total surplus(%)	-1.1	-3.2
	Airline level	
	CSA airlines	Non-CSA airlines
Δ Fare (%)	21.6	15.4
Δ flight frequency (%)	7.2	4.2
Δ Passenger volume (%)	-19.2	2.8
Δ Producer surplus (%)	5.1	14.8

Note: Effects are measured as the difference of outcomes from equilibrium without CSA and equilibrium with CSA. In the first panel, we compute two equilibria: one under *horizontal CSA* and the other under the full CSA. In the second panel, we use the full-CSA equilibrium, but decompose it to the CSA-related products and Non-CSA products.

6.1 CSA and regulation on capital stake holding

We have so far examined how CSA would affect market competition in our setting. In this subsection, we focus on another salient market structure, cross ownership. In particular, we examine the relationship between CSA and regulation on capital stake for an application to competition policy. As we describe in 2, the Japanese authority restricts the amount of capitals hold by domestic competitors to less than 20%. This restriction, implemented in 2010, may not accommodate the impact of CSA. We try to examine how the CSA can be related to inter-airline capital holding and capital regulation.

We focus on the price effect of those two market structures. Specifically, we calculate a price elasticity with respect to the parameters λ and κ, by counterfactual simulation. By looking at the price elasticity of these parameters, we can quantify the price effect of those market structures in a compatible way. The reason that we focus on the price effect is based on the previous result: whether introducing the endogenous quality or not, the price increase caused by CSA is so significant. That observation leads us to solely considering impact on prices.

Formally, for product j, we compute the price elasticity with respect to the two parameters as

$$\eta_j^\lambda = \frac{\Delta_j^p}{\Delta_\lambda}\frac{\lambda}{p_j}$$
$$\eta_j^\kappa = \frac{\Delta_j^p}{\Delta_\kappa}\frac{\kappa}{p_j}$$

where $\Delta_\lambda, \Delta_\kappa$ denotes the change in parameters, and Δ_j^p represents the price change as a result of change in market structure. We consider 1% change in CSA and capital stakes to simulate the price change. The set of products considered here is the same as the previous set of ones within the 20 markets.

The result is as follows. The average of η^λ is equal to 0.16 with standard deviation 2.04, whereas the average of η_j^κ is equal to 0.12 with standard deviation 0.46. In short, the market price is inelastic with respect to both parameters, compared to price elasticity of demand: a one percent increase in λ, the degree of codeshare, would induce only 0.16% percent increase in price, and one percent increase in κ, the capital stake owned by a competing airline, would raise price by 0.12%, on average.

From the price elasticity measures, we can derive the substitution between λ and κ as $\frac{\eta^\kappa}{\eta^\lambda}$, which is equal to 1.15 on average value. It represents how much κ is needed to compensate the price change caused by 1% increase in λ. Combining this substitution measure with estimates $\widehat{\lambda}$ and data on κ, we can compute the *effective increase in capital stake* measured by price increase, in the presence of CSA.

Figure 5 shows the actual values of κ and *effective increases in* κ for three airlines:

ADO, SFJ, and SNA, all of which are associated with ANA by CSA and capital relationship. The black bars represent the actual share of capital hold by ANA at each point. They are below the regulation maximum of 0.2 for all time, as the dotted horizontal line shows. The gray bar is the effective capital share, consisting of the actual capital share and the *effective increase* induced by CSA. After 2013, when the regulation was eased and the degree of CSA was enhanced to nearly 40%, the effective capital share has almost doubled, ranging from 30 to 40% across the three airlines. Observing this vivid change, we can argue that the regulation on capital ownership is essentially bypassed by introducing and strengthening CSA.

Although we have argued the anti-competitive aspect of CSA in relation to regulation, notice that our approach may include some caveat. First, by solely focusing on the price effect, we are abstracting away much of the market interactions caused by CSA and cross ownership. While our results suggest disproportionately large effect via price, such an inference may not hold in general settings.

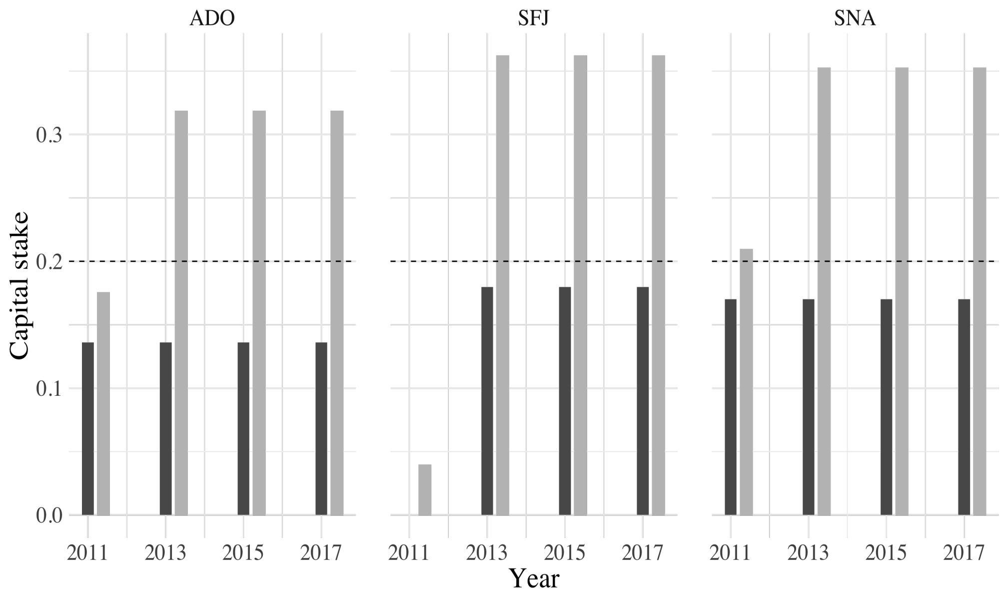
Also, beyond the validity of approach, our measure is only static, in short term, which can conceal an important point. For example, by bailing out airlines, CSA may allows them to continue their aviation service, thus contributing to the airline network and consumer benefit in longer term. In fact, Japanese Fair Trade commissioner (JFTC) approved the first CSA between ADO and ANA in 2002, partly because of the business crisis of ADO. When perceived as a means to enhance airline network, our static approach can underestimate the benefit of CSA.

7 Conclusion

In this paper, we construct and estimate a structural model that incorporates CSA. The supply-side model shows that we can obtain a nontrivial form of markup for each product, if we consider the vertical relationship induced by CSA. The detailed data and regulatory information on the Japanese domestic airline industry allows us to estimate the code-sharing parameter and examine the airline behavior. Using the estimated model, we carry out a counterfactual simulation to quantify the impact of CSA on the market outcomes and social welfare. The simulation result shows that the agreements dampen competition particularly by raising market fares, resulting in steep decline in consumer welfare. Endogenizing flight frequency alleviates the welfare loss via increasing product qualities, while such enhancement is limited.

A potential application of the present study is for slot-allocation problem. In Japan, slots in Haneda airport, the most congested domestic airport, are allocated to airlines every five years. The allocation mechanism differs from the international convention,

Figure 5: The effective increase of capital stake holding caused by CSA



Note: The black bars depict the actual shares of the capital hold by ANA. The gray bars depict the sums of the actual capital share and the *effective increase in capital share* caused by CSA, which is measured in terms of price change. The horizontal dotted line is at 0.2, the regulation on the amount of capital holding by a competing airline.

which is based on the IATA guideline: the assessment reports published by MLIT outline the allocation standards, which span from travel security level to the contribution to competitive environment. Those measures may not fully take into account the market structure of CSA and capital relationship. Hence, it is a relevant question whether the current procedure can lead to the optimal allocation and, if not, how we can achieve it.

Our study has at least two limitations. First, the definition of a product is coarse in the empirical analysis. We aggregate flight level characteristics, such as departure time or fares into one product. Also, the ticket level information such as advanced purchase discount is ignored in the data construction. More accurate data is required to further assess the consumer behavior in micro level.

The second limitation is the static treatment of the agreement formation. Our structural model and counterfactual simulation assumes that CSA is exogenously determined. It is more likely that the airlines negotiate the agreement contracts and route coverage based on their expectation of future market and competition, as in the airline network of formation (Aguirregabiria and Ho 2012). Such an analysis will require the estimation of a dynamic game. We believe it can deepen our understanding of the nature of airline competition and network structure. More research needs to be done in these areas.

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Appendix A Additional tables

In this section, we provide additional tables ommited from the above argument.

Appendix A.1 Data description

Table A1 shows the inter-airline relationship in the domestic airline market. Table A2 shows the information available from timetable data.

Table A1 has five columns: in the first column each airline name is represented by a three-letter code, and in the second the capital share of the firm owned by the group leader is presented. The third and forth columns show whether the airline is Low-cost carrier (LCC) and commuter carrier, who serves only the regional routes[8]. The fifth column shows the number of routes that the airline flies at least one aircraft per day, indicating the relative size of each airline.

8. In this paper, we define regional routes as routes that do not include main cities, such as Tokyo, Osaka and Fukuoka.

Table A1: Overview of inter-airline relationships in 2017

airline	% of capital share	Low-cost carrier	commuter carrier	number of routes serving
		Panel A : ANA		
ANA		No	No	224
SKY	16.5	Yes	No	38
APJ	77.9	Yes	No	26
ADO	13.61	No	No	21
SNA	17.03	No	No	20
SFJ	17.96	No	No	10
VNL	100	Yes	No	10
ORC	5.6	No	Yes	8
		Panel B : JAL		
JAL		No	No	138
JAC	60	No	Yes	38
JJP	33.3	Yes	No	32
JTA	72.8	No	Yes	21
RAC	74.5	No	Yes	16
SJO	5	Yes	No	8
		Panel C : Others		
IBX		No	Yes	20
FDA		No	Yes	9
AMX		No	Yes	8

Appendix B Model description

Appendix B.1 Solution to the full-assumption model

In this subsection, we discuss the supply-side model with full assumptions and its solution. The model in this paper's body exclude the assumption of capital stake relationship between airlines, which would induces partial ownership. Since we have the exact capital share hold by airlines (see Table A1), considering capital stake does not change the dimension of parameters of interest nor the inutition of our model; however, the composition of the price-cost margins and resulting moment condition have to be modified due to the change in the incentive structure.

Suppose that we have a market with two competing airlines A, B and three products a, b, and c. The first two products are the single-carrier products of airlines A, B,

Table A2: Example of timetable data for a hypothetical route from AAA to BBB

Period	departure&arrival time	flight ID	plane ID	operating firm	marketing firm
2011Q1	06:55 - 08:30	503	772	JAL	-
2011Q1	09:00 - 10:30	51	74P	ANA	-
2011Q1	10:25 - 12:05	507	7J2	ADO	ANA
2011Q1	12:00 - 13:35	53	74P	ADO	-
2011Q1	15:00 - 16:40	509	773	JAL	-

respectively. The product c is code-shared: the airline A operates the aircraft, and airline B sells $\lambda \in (0, 1)$ portion of it to the consumer.

Further, we assume that the airline B has $\kappa \in (0, 1)$ portion of capital stake of airline A. As we present in A1, certain amount of stake of many domestic airlines are hold by either of two predominant players, ANA or JAL. This fact, combined with the practice of CSA described in Section 2, naturally leads to the formulation of a bilateral capital relationship κ. That is, the airline B is aware of the κ-share of the profit flow from the airline A.

To model such incentive structure, we follow the strategy in O'Brien (2000). The partial equity stake holding yields an unilateral pricing incentive for the airline B (equity holder), who cares the profit flow via the partial ownership[9]. This is the most general setting in our data set: only ANA or JAL hold the capital of competing airlines, and they do not provide aircraft for CSA. We can consider more general setting of mutual ownership, but that is out of the scope of this paper.

We first look at the downstream problem. Since the airline A has not capital of B, its problem is indifferent from the previous one:

$$\max_{p_a, p_c^a, f_a, f_c} \pi_A(\mathbf{p}, \mathbf{f}) = \left[(p_a - mc_a^p) \cdot q_a(\mathbf{p}, \mathbf{f}) - mc_a^f \cdot f_a + (1 - \lambda)(p_c^a - mc_c^p) \cdot q_c(\mathbf{p}, \mathbf{f}) - mc_c^f \cdot f_c\right]$$

for given w, p_b, and f_b,

9. We assume that those holding airlines does not have control over the airlines.

Hence, the FOC with respect to p_a, p_c^a are written as

$$0 = q_a(\mathbf{p}, \mathbf{f}) + \frac{\partial q_a}{\partial p_a}(\mathbf{p}, \mathbf{f})(p_a - mc_a^p) + \frac{\partial q_c}{\partial p_a}(\mathbf{p}, \mathbf{f}) \cdot (1-\lambda)(p_c^a - mc_c^p) \tag{B.1}$$

$$0 = (1-\lambda)\frac{\partial q_a}{\partial p_c}(\mathbf{p}, \mathbf{f})(p_a - mc_a^p) + (1-\lambda)\left[\frac{\partial q_c}{\partial p_c}(\mathbf{p}, \mathbf{f}) \cdot (1-\lambda)(p_c^a - mc_c^p) + q_c(\mathbf{p}, \mathbf{f})\right] \tag{B.2}$$

They are indifferent from the argument in the body because airline A do not hold any capital stake of the other airline. Remember that we use the relationship $p_c = (1-\lambda)p_c^a + \lambda p_c^b$.

Airline B's problem is written as

$$\max_{p_b, p_c^b, f_b} \left[(p_b - mc_b^p) \cdot q_b(\mathbf{p}, \mathbf{f}) - mc_b^f \cdot f_b + (p_c^b - w) \cdot \lambda q_c(\mathbf{p}, \mathbf{f}) + \kappa \pi_A(\mathbf{p}, \mathbf{f})\right] \quad \text{for given } p_a, p_c^a, w, f_a, f_c.$$

Here, we have an additional $\kappa \cdot \pi_A$ term for airline B's profit function because of the cross ownership. This changes B's incentive structure.

Putting aside the flight frequency, the first-order conditions with respect to fare are as follows.

$$\begin{aligned} 0 &= q_b(\mathbf{p}, \mathbf{f}) + \frac{\partial q_b}{\partial p_b}(\mathbf{p}, \mathbf{f})(p_b - mc_b^p) + \lambda \frac{\partial q_c}{\partial p_b}(\mathbf{p}, \mathbf{f})(p_c^b - w) \qquad \text{(B.3)} \\ &\quad + \kappa \left(\frac{\partial q_a}{\partial p_b}(p_a - mc_a^p) + (1-\lambda)\frac{\partial q_c}{\partial p_b} \right) \\ 0 &= \lambda \frac{\partial q_b}{\partial p_c}(\mathbf{p}, \mathbf{f})(p_b - mc_b^p) + \lambda\{\lambda \frac{\partial q_c}{\partial p_c}(\mathbf{p}, \mathbf{f})(p_c^b - w) + q_c(\mathbf{p}, \mathbf{f})\} \qquad \text{(B.4)} \\ &\quad + \kappa\lambda \left(\frac{\partial q_a}{\partial p_c}(p_a - mc_a^p) + (1-\lambda)\frac{\partial q_c}{\partial p_c}(p_c^a - mc_c^p) \right) \end{aligned}$$

where Eq. (B.3) is for p_b and Eq. (B.4) for p_c^b. The intuition does not change much from the Eq. (8) and Eq. (9), except for the terms surrounded by large bracket: they represents the marginal revenue flow from the other airline's product via cross ownership. That, as discussed in O'Brien (2000), could lessen the competitive incentive because airline B enjoys larger profit from raising fares.

Combining these markup equations yields the following vector representation.

$$
\begin{pmatrix} p_a - mc_a^p \\ p_b - mc_b^p \\ p_c^a - mc_c^p \\ p_c^b - w \end{pmatrix} = -\left(\Omega^p(\kappa,\lambda) \otimes \Delta^p\right)^{-1} \tilde{\mathbf{q}} \qquad \Omega^p(\kappa,\lambda) \equiv \begin{pmatrix} 1 & 0 & 1-\lambda & 0 \\ \kappa & 1 & \kappa(1-\lambda) & \lambda \\ \frac{1}{1-\lambda} & 0 & 1 & 0 \\ \frac{\kappa}{\lambda} & \frac{1}{\lambda} & \kappa\frac{1-\lambda}{\lambda} & 1 \end{pmatrix} \tag{B.5}
$$

The ownership matrix represents (i) partial ownership (λ) due to CSA and (ii) cross ownership (κ) due to capital structure. The derivation of the upstream margin is almost same, and depicted in Appendix B.2. Then, we have the following price-cost margins.

$$
\mathbf{p} - \mathbf{mc^p} = -T\left(\Omega^p(\kappa,\lambda) \otimes \Delta^p\right)^{-1} \tilde{\mathbf{q}} + \begin{pmatrix} 0 \\ 0 \\ -\left(\frac{\partial q_c}{\partial w}\right) q_c(\mathbf{p},\mathbf{f}) \end{pmatrix} \tag{B.6}
$$

$$
\text{where} \quad \mathbf{p} = \begin{pmatrix} p_a \\ p_b \\ p_c \end{pmatrix}, \quad \mathbf{mc^p} = \begin{pmatrix} mc_a^p \\ mc_b^p \\ mc_c^p \end{pmatrix}
$$

The FOCs with respect to flight frequency are also written as

$$
mc_a^f = \frac{\partial}{\partial f_a} q_a(p_a - mc_a^p) + (1-\lambda)\frac{\partial}{\partial f_a} q_c(p_c^a - mc_c^p) \tag{B.7}
$$

$$
\begin{aligned} mc_b^f = &\frac{\partial}{\partial f_b} q_b(p_b - mc_b^p) + \lambda \frac{\partial}{\partial f_b} q_c(p_c^b - w) + \\ &\kappa\left(\frac{\partial q_a}{\partial f_b}(p_a - mc_a^p) + (1-\lambda)\frac{\partial q_c}{\partial f_b}(p_c^a - mc_c^p)\right) \end{aligned} \tag{B.8}
$$

$$
mc_c^f = \frac{\partial}{\partial f_c} q_a(p_a - mc_a^p) + (1-\lambda)\frac{\partial}{\partial f_c} q_c(\mathbf{p},\mathbf{f}) \tag{B.9}
$$

which can be summarized into the following vector representation.

$$\mathbf{mc^f} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \left[\Omega^f(\kappa,\lambda) \times \Delta^f\right] \begin{pmatrix} p_a - mc_a^p \\ p_b - mc_b^b \\ p_c^a - mc_c^p \\ p_c^b - w \end{pmatrix} \tag{B.10}$$

$$\text{where} \quad \Omega^f(\kappa,\lambda) = \begin{pmatrix} 1 & 0 & 1-\lambda & 0 \\ \kappa & 1 & \kappa(1-\lambda) & \lambda \\ \frac{1}{1-\lambda} & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

Appendix B.2 wholesale price derivatives

The derivation follows the method proposed by Villas-Boas (2007).

Again, we continue to stick to the simple market describe in Section 4.2. Recall that the upstream problem is expressed as

$$\begin{aligned} &\max_w \lambda(w - mc_c^p) q_c(\mathbf{p}, \mathbf{f}) \\ &\text{subject to } p_c^b = p_c^b(w) \end{aligned} \tag{B.11}$$

The first-order condition with respect to p_c^b works as the constraint. The upstream airline A decides the wholesale price, knowing its effect on the downstream product price.

$$0 = \frac{\partial q_b}{\partial p_c}(\mathbf{p}, \mathbf{f})(p_b - mc_b^p) + \left(\lambda \frac{\partial q_c}{\partial p_c}(\mathbf{p}, \mathbf{f})(p_c^b - w) + q_c(\mathbf{p}, \mathbf{f})\right)$$

The solution to this problem is

$$w^* = mc_c^p + \left(-\frac{\partial q_c}{\partial w}\right)^{-1} q_c(\mathbf{p}, \mathbf{f}).$$

Thus, the remaining problem is to derive $\frac{\partial q_c}{\partial w}$.

Since we assume a special vertical structure where the upstream airline only knows that p_c^b depends on w, the rest of the downstream fares are fixed. By totally differentiating this equation with respect to downstream fare p_c^b and wholesale price w, we obtain the following price derivatives with respect to the wholesale price.

$$0 = dp_c^b \left(\frac{\partial}{\partial p_c^2} q_b(\mathbf{p})(p_b - mc_b) + \frac{\partial}{\partial p_c^2} q_c(\mathbf{p}) \cdot \lambda(p_c^b - w) + \frac{\partial}{\partial p_c} q_c(\mathbf{p})(1+\lambda) \right) \cdot \lambda - \lambda \frac{\partial q_c}{\partial p_c} dw$$

$$\frac{\mathrm{d}p_c^b}{\mathrm{d}w} = \left(\frac{\partial}{\partial p_c^2} q_b(\mathbf{p})(p_b - mc_b) + \frac{\partial}{\partial p_c^2} q_c(\mathbf{p}) \cdot \lambda(p_c^b - w) + \frac{\partial}{\partial p_c} q_c(\mathbf{p})(1+\lambda) \right)^{-1} \frac{\partial q_c}{\partial p_c} \quad \text{(B.12)}$$

which depends on the code-sharing parameter λ. Then, we can calculate the derivative with respect to wholesale price $\frac{\partial q_c}{\partial w}$ as

$$\begin{aligned} \frac{\partial q_c}{\partial w} &= \frac{\partial q_c}{\partial p_c} \cdot \frac{\partial p_c}{\partial p_c^b} \cdot \frac{\mathrm{d}p_c^b}{\mathrm{d}w} \\ &= \lambda \cdot \frac{\partial q_c}{\partial p_c} \cdot \frac{\mathrm{d}p_c^b}{\mathrm{d}w}. \end{aligned}$$