# Tax or Subsidy on Interregional Travel with Infectious Diseases*

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## Abstract

This paper develops a two-region model of interregional travel with infectious diseases and analyzes the optimal policy intervention. The main result is that even when infection spreads, both the restriction and promotion of travel may be optimal depending on regional asymmetry. This stems from the bidirectionality of interregional travel and the difficulty of identifying infected but asymptomatic from noninfected individuals. Numerical examples show that both taxes and subsidies on travel could be optimal in a realistic range of parameter values.



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# 1 Introduction

Due to the coronavirus disease 2019 (COVID-19) pandemic, many countries have restricted the inter- and intranational movement of people. Some countries, however, have adopted the opposite policies (World Tourism Organization, 2020). For example, the Japanese government initiated a travel promotion campaign (the `Go To Travel' campaign) in July 2020, when the COVID-19 pandemic had yet to recede in the country.[1] Motivated by policy variations, this paper considers how to intervene in travel between regions where infection spreads.

This paper develops a two-region model of interregional travel with infectious diseases. The model is base on the setting used in the theoretical literature of air passenger

[1] The campaign offers 35 percent discounts on travel costs and additionally issues coupons equivalent to 15 percent of the costs that can be used for consumption at the destination. The government initially appropriated approximately 1.12 trillion JPY (roughly equivalent to 112 billion USD) for the campaign and added 0.31 trillion JPY (roughly 31 billion USD) in December 2020.

transport market (e.g., Brueckner, 2002; Brueckner 2004; Czerny and Zhang, 2015) and incorporates infectious diseases into it. The optimal tax on travel is then derived for the model, indicating whether, in the context of infectious disease, a government should always tax (i.e., restrict) interregional movement or subsidize (i.e., promote) it in some cases.

The main result is that the optimal tax could be not only positive but also negative (i.e., a subsidy) even when an infection spreads, suggesting that restriction of interregional movement is not always appropriate and that the promotion of movement is socially optimal in some cases. The signs and magnitudes of the travel externalities change according to the direction of a travel and the infectious status of a traveler. The asymmetry between regions also plays an important role to determine the externalities.

The externality may be positive due to two features of the market: (i) the bidirectionality of interregional travel and (ii) the difficulty of distinguishing infected (but not symptomatic) residents from noninfected residents. First, people travel between two regions in both directions. If travel from region A to region B increase the probability that a person is infected or infects others, travel from B to A may decrease it. When the latter effect is sufficiently large, a subsidy on travel may be optimal. As implied by this argument, regional asymmetry in infectious diseases plays a central role in determining the optimal tax.

Second, it is difficult to distinguish noninfected and infected residents. The probability that a noninfected individual becomes infected is lower when they are active in the safer region where the infection is less widespread. However, an infected individual increases infection cases less when active in the *riskier* region. Since the people with whom the infected individual comes into contact are more likely to already be infected in the riskier region, these contacts are less likely to cause additional infections. Therefore, to reduce infectious disease, a government wants noninfected individuals to be in the safer region and wants infected individuals to be in the riskier region. According to the balance of these incentives, both a tax and a subsidy could be optimal when it is impossible to identify the infectious status of residents.

Numerical examples show that the optimal tax could indeed be negative with parameter values in a realistic range, which are set in line with the case of Japan in 2020. The optimal rate is, however, calculated to be small and at most on the order of 10 JPY (approximately 0.1 USD). Therefore, this result hardly supports the large subsidy in Japan, although it relies on a simple theoretical model and should be interpreted with caution.

**Related literature.**

This paper is closely related to empirical studies that analyze the effects of restrictions on interregional mobility on the spatial spread of COVID-19. The literature often focuses on how mobility restrictions to/from a region with high levels of infection transmission can suppress the spread of infectious diseases into other regions (e.g., Chinazzi et al., 2020; Fang et al., 2020). However, restrictions on movement to/from the epicenter might increase infectious cases in that region, as some studies point out (e.g., Kondo, 2021). When mobility is restricted, noninfected residents of the epicenter cannot escape to safer regions, and infected residents must stay in the region and spread infectious diseases there. This paper theoretically investigates the nature of externalities of travel under a pandemic and considers the optimal policy from the total welfare of all regions. The results indicate that since the effects of mobility restrictions on the epicenter may outweigh those on another region under certain circumstances, not restriction but promotion of movement may be optimal.

Externalities of travel have been widely studied. While travelers contribute to the destination economy, they may accompany negative effects (e.g., Dwyer and Forsyth, 1993). Negative externalities of travel include congestion (Palmer-Tous et al., 2007; Saenz-de-Miera and Rosselló, 2012), accidents (Page and Meyer, 1996), air pollution (Saenz-de-Miera and Rosselló, 2014), crime (Biagi and Detotto, 2014), and water shortage (Sheng et al., 2017). To our knowledge, however, the literature has not focused on infectious diseases as a source of externalities of travel. This paper theoretically investigates the nature of externalities of travel regarding infectious diseases, showing that the externality depends on the direction of a travel and the infectious status of a traveler and may be positive.

Studies in the literature on knowledge spillover and brain drain also investigate externalities of movement of people. A region's productivity increases when research facilities are located there (e.g., Audretsch and Lehmann, 2005) and entrepreneurs move to the region (e.g., Gibson and Makenzie, 2014). There have also been studies on the interregional externalities of movement of higher educated or skilled workers (e.g., Leach, 1996; Justman and Thisse, 2000). These studies and the present study differ in the nature of movement analyzed. The former is for the longer-term and one-way movement (i.e., migration), while the latter focuses on the shorter-term and round-trip movement (i.e., travel). In the context of travel, effects that a traveler takes away from the destination to the origin region (e.g., a traveler gets infected during travel and then infects others after coming back home) are relevant. This paper therefore uses a framework that takes those effects into account to investigate the externalties of travel regarding infectious diseases.

**Structure of the article.**

The remainder of this paper is organized as follows. Section 2 describes the model. Section 3 explores the optimal tax on interregional movement. Section 4 provides numerical examples. Section 5 concludes the paper.

# 2 Model

This section introduces a model to analyze taxes on interregional travel in the presence of infectious diseases. The model consists of two regions, labeled 1 and 2, and a central government. Each region has two types of residents: "decision-maker" and "non-decision-maker." The decision-makers decide whether to stay at their residence or travel to the other region. The non-decision-makers are assumed to always stay. An interpretation of the non-decision-makers is that they provide services for travelers, for example, in entertainment districts and sightseeing spots. The number of decision-makers and non-decision-makers in region $i$ is denoted by $N_i$ and $\overline{N}_i$, respectively.

We analyze a two-stage game and its subgame perfect Nash equilibrium. In the first stage, the government sets the tax (or subsidy) rate. In the second stage, the decision-makers decide whether to stay or travel. Infection then spreads as explained below. At the end of the second stage, it turns out who are infected.

Infectious diseases are modeled as described below and illustrated in Figure 1. First, the probability that a resident in region $i$ is already infected at the beginning of the game is $n_i/N_i$. This means that the number of infected decision-makers is $n_i$ and that of infected non-decision-makers is $\overline{N}_i n_i/N_i$. Second, no residents know whether they are already infected when making their decisions. A possible interpretation of this is that the infected residents are in the incubation period. Third, the probability that a noninfected

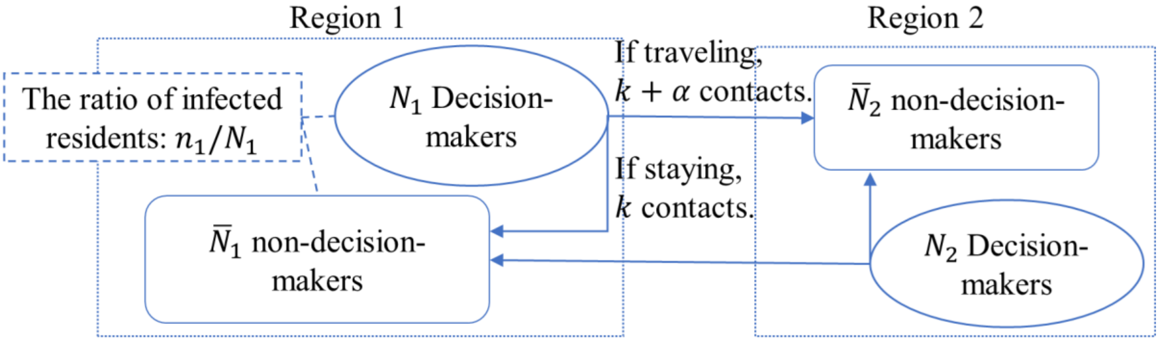


Figure 1
Modeling of Infection

resident becomes infected when coming into contact with an infected individual in region $i$ is $r_i$. What matters is not their places of residence but where the contact takes place because the probability of transmission is plausibly determined by the climate of the place of contact. Fourth, a decision-maker comes into contact with non-decision-makers. Specifically, when choosing to stay, a decision-maker in region $i$ consumes services provided by non-decision-makers in region $i$ and is exposed to them; when travel is chosen, the decision-maker comes into contact with non-decision-makers in the other region. Fifth, the number of people with whom a decision-maker comes into contact is allowed to differ across stay ($k$) and travel ($k+\alpha$). Sixth, a decision-maker who becomes infected during travel experiences the onset of symptoms after returning home.

Under these assumptions, the probability that a noninfected (i.e., susceptible) decision-maker becomes infected can be calculated. Additionally, the expected number of additional infections that an infected decision-maker will cause can be derived. Table 1 summarizes these probabilities and expectations, which play an important role in understanding the optimal tax and are referred to several times in the rest of the paper. The upper row shows the probability that a susceptible decision-maker from region $i$ is *not* infected. If deciding to stay, a susceptible decision-maker becomes infected when

Table 1
Probability and expectation regarding infection

| (For decision-makers in region $i$) | Stay in $i$ | Travel to $-i$ |
|---|---|---|
| Probability of a susceptible decision-maker *not* to be infected | $\left(1-\frac{n_i}{N_i}r_i\right)^k$ | $\left(1-\frac{n_{-i}}{N_{-i}}r_{-i}\right)^{k+\alpha}$ |
| Expected additional infections by an infected decision-maker | $k\left(1-\frac{n_i}{N_i}\right)r_i$ | $(k+\alpha)\left(1-\frac{n_{-i}}{N_{-i}}\right)r_{-i}$ |

coming into contact with a non-decision-maker with a probability of $(n_i/N_i)r_i$, where $n_i/N_i$ is the probability that the non-decision-maker is infected and $r_i$ is the probability of transmission. The probability that the susceptible individual is not infected by a contact is therefore $1-(n_i/N_i)r_i$. Since the number of contacts is $k$ in the stay case, the probability of not being infected is $1-(n_i/N_i)r_i$ to the power of $k$. In the travel case, a susceptible decision-maker becomes infected when coming into contact with a non-decision-maker in the other region, denoted by $-i$, with the probability of $(n_{-i}/N_{-i})r_{-i}$. The probability of not being infected is thus $1-(n_{-i}/N_{-i})r_{-i}$ to the power of $k+\alpha$.

The lower row of Table 1 presents the expected number of additional infections caused by an infected decision-maker. In the stay case, a contact between an infected decision-maker and a non-decision-maker brings about an additional infection with a probability of $(1-n_i/N_i)r_i$, where $1-n_i/N_i$ represents the probability that the non-decision-maker is not yet infected. Since the infected decision-maker comes into contact with $k$ residents, the expected number is $k(1-n_i/N_i)r_i$. In the travel case, because the conditions in region $-i$ is relevant and because the number of contacts changes to $k+\alpha$, the expected number is $(k+\alpha)(1-n_{-i}/N_{-i})r_{-i}$.

A resident's utility is based on the setting used in the theoretical literature on air travel market (e.g., Brueckner, 2002; Brueckner 2004; Czerny and Zhang, 2015) and incorporates infectious diseases. The utility depends on consumption of goods other than travel, benefits from travel, and damages from infection:

$$U = y + \Theta(-A + b) - \Psi d,$$

where $y$ is income, $\Theta$ takes value one if an individual travels and zero otherwise, $A$ is the tax (or subsidy if negative) on travel, $b$ represents benefits from traveling and is uniformly distributed on the interval $[B - h, B]$, $\Psi$ takes value one if infected and zero otherwise, and $d$ denotes the damages from infection, including physical and psychological damages and income losses. To simplify the model, the monetary costs of travel are assumed to be zero.[2] Accordingly, $y - \Theta A$ equals nontravel consumption expenditure.

A decision-maker chooses one of two options based on expected utility since the infection status $\Psi$ is uncertain at the time of decision. For a decision-maker from region $i$, the expected utility from traveling is

$$u_{T,i}^{b} = y - A + b - \left[\frac{n_i}{N_i} + \left(1 - \frac{n_i}{N_i}\right)\left\{1 - \left(1 - \frac{n_{-i}}{N_{-i}} r_{-i}\right)^{k+\alpha}\right\}\right] d.$$

The probability of being infected at the end of the second stage appears in the square brackets. The first term is the probability that the decision-maker is already infected, which is not yet revealed. The second term is the probability that the decision-maker is not initially infected, $1 - n_i/N_i$, multiplied by the probability of becoming infected during travel to region $-i$, $1 - (1 - n_{-i} r_{-i}/N_{-i})^{k+\alpha}$ (see Table 1). Similarly, the expected utility from staying is

$$u_{S,i} = y - \left[\frac{n_i}{N_i} + \left(1 - \frac{n_i}{N_i}\right)\left\{1 - \left(1 - \frac{n_i}{N_i} r_i\right)^{k}\right\}\right] d.$$

The central government maximizes the social surplus $W$, defined as the sum of the

[2] Alternatively, $b$ can be interpreted as a net benefit, that is, the travel benefits minus the travel costs. The results do not change when the travel costs are instead explicitly modeled.

residents' expected utilities and the fiscal surplus:

$$W = \sum_{i=1,2}\left[N_i \int_{B-h}^{B} \max\{u_{T,i}^b, u_{S,i}\}\frac{1}{h}db + \bar{N}_i\{y - Prob_i(\Psi = 1)d\}\right] + Fiscal\ Surplus.$$

The first term in square brackets represents the sum of expected utilities for the decision-makers in region $i$. The second term is that of the non-decision-makers, where $Prob_i(\Psi = 1)$ represents the probability that a non-decision-maker in region $i$ is infected at the end of the second stage and depends on the number of travelers to/from the region. Note that $\bar{N}_i\, Prob_i(\Psi = 1)$ represents the expected number of infected non-decision-makers in region $i$. Accordingly, using the expected number of additional infections caused by an infected decision-maker shown in Table 1, it can be replaced by

$$\bar{N}_i\, Prob_i(\Psi = 1) = \bar{N}_i \tfrac{n_i}{N_i} + (N_i - q_i)\tfrac{n_i}{N_i} k\left(1 - \tfrac{n_i}{N_i}\right) r_i + q_{-i}\tfrac{n_{-i}}{N_{-i}}(k + \alpha)\left(1 - \tfrac{n_i}{N_i}\right) r_i,$$

where $q_i$ denotes the number of travelers from region $i$ to region $-i$, $(N_i - q_i)n_i/N_i$ is the number of infected decision-makers who stay in region $i$, and $q_{-i}n_{-i}/N_{-i}$ is the number of infected travelers from region $-i$.[3]

The fiscal surplus is

$$Fiscal\ Surplus = \sum_{i=1,2}(Aq_i - D_iC_i)\,,$$ [4]

where $D_i$ represents government expenditures per infection, including costs of medical

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[3] To express the expected number as above, we implicitly assume that $\bar{N}_i$ is sufficiently large relative to $n_i$, which is sufficient to assume $kn_i + (k + \alpha)n_{-i} < \bar{N}_i$, and that a nondecision-maker comes into contact with a decision-maker once at most.

[4] When the government provides private consumption goods uniformly for the residents, its budget constraint is $\sum_{i=1,2}\{Aq_i - D_iC_i - (N_i + \bar{N}_i)g\} = 0$, where $g$ is the publicly provided private goods per resident. If $g$ is assumed to be simply added to the utilities, that is, $y + \Theta(-A + b) - \Psi d + g$, the same results are obtained.

treatment and administration regarding infection control, and $C_i$ is the number of infected residents of region $i$:

$$C_i = n_i + \bar{N}_i \frac{n_i}{N_i} + (N_i - q_i)\left(1 - \frac{n_i}{N_i}\right)\left\{1 - \left(1 - \frac{n_i}{N_i} r_i\right)^k\right\}$$
$$+ q_i \left(1 - \frac{n_i}{N_i}\right)\left\{1 - \left(1 - \frac{n_{-i}}{N_{-i}} r_{-i}\right)^{k+\alpha}\right\} + (N_i - q_i)\frac{n_i}{N_i} k \left(1 - \frac{n_i}{N_i}\right) r_i$$
$$+ q_{-i} \frac{n_{-i}}{N_{-i}} (k + \alpha)\left(1 - \frac{n_i}{N_i}\right) r_i.$$

The first and second terms represent the number of initial infections for decision-makers and non-decision-makers, respectively. The third and fourth terms are the number of decision-makers in region $i$ who are not initially infected but become infected while staying or traveling, respectively (see Table 1). The fifth and sixth terms are the number of non-decision-makers in region $i$ who are not initially infected but become infected by staying decision-makers from region $i$ and travelers from region $-i$, respectively (see again Table 1).

This model incorporates two kinds of externalities regarding infection. One is for susceptible decision-makers. When a susceptible individual becomes infected, government expenditures, $D_i$, are required in addition to private costs, $d$. The second is for infected individuals. Although an infected decision-maker has no private damage from infecting others, the damages suffered by the infected individuals, $d$, and the associated government expenditures, $D_i$, are counted as external costs. As summarized in Table 1, a decision on whether to stay or travel changes both the probability of a susceptible decision-maker becoming infected and the expected number of additional infections caused by an infected decision-maker. However, since decision-makers do not consider external costs, their choices may deviate from the socially optimal choices. Susceptible decision-makers may choose an option with a higher probability of infection than the socially optimal option. Additionally, infected decision-makers may choose an option with a larger expected number of additional infections. The next section considers the optimal policy intervention to address these externalities.

# 3 Optimal Travel Tax

This section discusses the optimal tax in the model. Subsection 3.1 characterizes the subgame perfect Nash equilibrium. Subsection 3.2 investigates how the optimal tax varies according to conditions of infection.

## *3.1* Subgame perfect Nash equilibrium

This subsection derives the subgame perfect Nash equilibrium of the model. The second stage, in which decision-makers choose whether to stay or travel, is considered first. A decision-maker from region $i$ travels if the expected utility from traveling exceeds that from staying, that is,

$$u_{T,i}^{b} - u_{S,i} \geq 0$$
$$\Leftrightarrow b \geq A + \left(1 - \frac{n_i}{N_i}\right)\left\{1 - \left(1 - \frac{n_{-i}}{N_{-i}} r_{-i}\right)^{k+\alpha}\right\} d - \left(1 - \frac{n_i}{N_i}\right)\left\{1 - \left(1 - \frac{n_i}{N_i} r_i\right)^{k}\right\} d$$
$$\equiv \underline{b}_i \, .$$

Thus, decision-makers with a travel benefit above the threshold, $\underline{b}_i$, travel.[5] Accordingly, the number of travelers from region $i$ to region $-i$ is

[5] To avoid a situation in which every decision-maker chooses same action regardless of the government's choice, we assume that $B - h < \underline{b}_i < B, i = 1,2$.

$$q_i = \frac{N_i}{h}\left(B - \underline{b}_i\right)$$

$$= \frac{N_i}{h}\left[B - A - \left(1 - \frac{n_i}{N_i}\right)\left\{1 - \left(1 - \frac{n_{-i}}{N_{-i}} r_{-i}\right)^{k+\alpha}\right\} d + \left(1 - \frac{n_i}{N_i}\right)\left\{1 - \left(1 - \frac{n_i}{N_i} r_i\right)^{k}\right\} d\right].$$

The third term in brackets is the probability that a decision-maker from region $i$ becomes infected during travel to region $-i$ (see Table 1) multiplied by the damage from infection. As this probability increases, people hesitate to travel to region $-i$. The fourth term represents the probability that a decision-maker from region $i$ becomes infected when staying in region $i$ (see again Table 1) and is also multiplied by the damage. As this probability increases, decision-makers become more likely to travel to escape from region $i$. In addition, the number of travelers depends on the tax, $A$.

In the first stage, the government sets the tax rate to maximize social welfare, $W$, considering residents' decisions in the second stage.[6] From the first-order condition, $dW/dA = 0$, the optimal tax ($A^*$) is found to be

$$A^* = S_1 + S_2 + I_1 + I_2, \tag{1}$$

where

$$S_i \equiv \frac{N_i - n_i}{N_1 + N_2} D_i \left\{\left(1 - \frac{n_i}{N_i} r_i\right)^{k} - \left(1 - \frac{n_{-i}}{N_{-i}} r_{-i}\right)^{k+\alpha}\right\}$$

and

$$I_i \equiv \frac{n_i}{N_1 + N_2}\left\{-k\left(1 - \frac{n_i}{N_i}\right) r_i (D_i + d) + (k + \alpha)\left(1 - \frac{n_{-i}}{N_{-i}}\right) r_{-i}(D_{-i} + d)\right\}.$$

The second-order condition is always satisfied as $d^2W/dA^2 = \left(-N_i - N_j\right)/h < 0$.

The four components of the optimal tax correspond to the government's four incentives to address externalities regarding infection. The externality arising from the

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[6] Using the notation of the threshold of $\underline{b}_i$, the sum of expected utilities of decision-makers in region $i$ reduces to $N_i \int_{B-h}^{B} \max\{u_{T,i}^b, u_{S,i}\}/h\, db = N_i \int_{B-h}^{\underline{b}_i} u_{S,i}/h\, db + N_i \int_{\underline{b}_i}^{B} u_{T,i}^b/h\, db$.

behaviors of susceptible decision-makers in region $i$ is addressed by $S_i$. The first term in curly braces in the equation for $S_i$ represents the probability that a susceptible decision-maker is *not* infected if choosing to stay. The second term is the probability of *not* being infected during travel. The difference thus represents how the probability of being infected is changed by travel. Although the private costs ($d$) associated with this change in the probability of infection are considered in deciding whether to travel, government expenditures ($D_i$) are not. The government therefore has an incentive to have susceptible decision-makers internalize these external costs. This incentive is represented by $S_i$ and weighted by the number of susceptible decision-makers in region $i$ $(N_i - n_i)$ among all decision-makers $(N_1 + N_2)$.

The externality arising from the behaviors of already infected decision-makers is addressed by $I_i$. The two terms in curly braces in the equation for $I_i$ represent the expected number of additional infections caused by an infected individual (see Table 1) multiplied by the sum of government expenditures ($D_i$ or $D_{-i}$) and private costs ($d$) in the cases of staying and traveling, respectively. The difference between the terms in braces therefore reflects the change in social costs due to travel by an infected individual. Since the costs are entirely external for infected decision-makers, the government has an incentive to have them internalize these costs. The ratio of targeted individuals, $n_i/(N_1 + N_2)$, is multiplied as the weight for $I_i$.

Obviously, in the absence of infectious disease (i.e., $n_1 = n_2 = 0$), all components of $A^*$ are zero. Since no externality exists, the government has no incentive to intervene in the decisions of residents. The next subsection discusses $A^*$ in the presence of infectious diseases (i.e., $n_1 > 0$ and/or $n_2 > 0$).

## 3.2 Optimal tax with infectious diseases

This subsection analyzes how $A^*$ varies according to the conditions regarding infectious diseases. First, the situation where travel significantly increases contacts with others (i.e., $\alpha$ is large) is briefly discussed. Then, we consider in detail situations with $\alpha = 0$: the case of symmetric regions, the cases where one of the parameters is asymmetric, and some cases where more parameters are asymmetric.

To our knowledge, there is no consensus regarding whether people come into more contact with others when they travel than when they remain in the place of residence. Naturally, the size of the parameter representing it ($\alpha$) affects $A^*$. As $\alpha$ increases, the probability that a susceptible decision-maker becomes infected during travel increases, resulting in positive values of $S_i$ due to the negative externality of travel. Additionally, with a sufficiently large $\alpha$, the large expected number of additional infections caused by travel by an infected decision-maker results in a positive $I_i$. Not surprisingly, the optimal policy is therefore to reduce travel (i.e., $A^* > 0$) when $\alpha$ is sufficiently large. The focus in the remainder of this subsection is on situations with $\alpha = 0$. We consider whether externalities persist and should be addressed by a tax or subsidy even when the number of contacts with others does not differ between the stay and travel cases. In addition, understanding factors determining $A^*$ other than $\alpha$ is another purpose of the following investigation.

When $\alpha = 0$, each component of $A^*$ reduces to the forms summarized in Table 2. The table highlights an interesting nature of the interregional travel market. First, the values in the curly braces in the equations for $S_1$ and $S_2$ have the same absolute value but the opposite signs. This means that if the probability of a susceptible decision-maker being infected is increased by travel from region 1 to 2, travel in the opposite direction

Table 2
Components of $A^*$ with $\alpha = 0$

| $i$ | $S_i$ | $I_i$ |
|---|---|---|
| 1 | $\frac{N_1 - n_1}{N_1 + N_2} D_1 \left\{ \left(1 - \frac{n_1}{N_1} r_1\right)^k - \left(1 - \frac{n_2}{N_2} r_2\right)^k \right\}$ | $\frac{n_1}{N_1 + N_2} \left\{ -k \left(1 - \frac{n_1}{N_1}\right) r_1 (D_1 + d) + k \left(1 - \frac{n_2}{N_2}\right) r_2 (D_2 + d) \right\}$ |
| 2 | $\frac{N_2 - n_2}{N_1 + N_2} D_2 \left\{ \left(1 - \frac{n_2}{N_2} r_2\right)^k - \left(1 - \frac{n_1}{N_1} r_1\right)^k \right\}$ | $\frac{n_2}{N_1 + N_2} \left\{ -k \left(1 - \frac{n_2}{N_2}\right) r_2 (D_2 + d) + k \left(1 - \frac{n_1}{N_1}\right) r_1 (D_1 + d) \right\}$ |

decreases the probability by the same amount. Second, the values in curly braces in the equations for $I_1$ and $I_2$ also have the same absolute value but the opposite signs. This indicates that if social costs are increased by an infected individual's travel from region 1 to 2, travel in the opposite direction decreases social costs by the same amount. These facts reflect the bidirectional nature of the interregional travel market, which plays an important role in understanding $A^*$.

A straightforward result found from Table 2 is that $A^* = 0$ when the regions are symmetric in the four parameters ($n_i$, $N_i$, $r_i$, and $D_i$) with $\alpha = 0$. If the regions are symmetric, the probability that a susceptible decision-maker becomes infected does not differ between the stay and travel cases. Accordingly, the value in parentheses in the equation for $S_i$, which represents the travel externality of a susceptible decision-maker, becomes zero. Additionally, the expected number of additional infections caused by an infected decision-maker is not changed by travel if the regions are symmetric. Accordingly, the value in parentheses in the equation for $I_i$, which represents the travel externality of an infected decision-maker, also becomes zero. This result is summarized as a proposition:

Proposition 1. When $n_1 = n_2, N_1 = N_2, r_1 = r_2, D_1 = D_2, and\ \alpha = 0$, then $A^* = 0$.

This proposition implies that even when infectious diseases spread rapidly (i.e., large values of $n_i$), the government does *not* need to intervene in the interregional travel market as long as the degree of the spread is symmetric (i.e., $n_1 = n_2$) with $\alpha = 0$.

However, A* becomes positive if infectious diseases spread asymmetrically (i.e., $n_1 \neq n_2$), even when $\alpha = 0$.

Proposition 2. When $n_1 \neq n_2, N_1 = N_2, r_1 = r_2, D_1 = D_2, and\ \alpha = 0$, then $A^* > 0$.

This proposition means that when infection spreads more in one region than in another, interregional travel should be discouraged. Although this may seem very natural, it is not as obvious if one recognizes the bidirectional nature of the travel market. The remark that trips to/from the risky region should be restricted is not enough, or even inaccurate, to prove the proposition. This is because, for example, susceptible decision-makers from the risky region can decrease their probability of being infected if they travel to the safer region and thus should be *encouraged* to travel by a subsidy.

To prove Proposition 2, Table 3 summarizes $S_i$ and $I_i$ in this situation. To explain specifically, it is assumed that region 1 is riskier than region 2 (i.e., $n_1 > n_2$). The signs of $S_2$ and $I_1$ are positive. Since susceptible decision-makers from the safer region (region 2) are more likely to be infected if they travel to the riskier region, their trips have a negative externality. The government thus has an incentive to discourage them ($S_2 > 0$).

Table 3
Case of proposition 2 with $n_1 > n_2$

| $i$ | $S_i$ | $I_i$ |
|---|---|---|
| 1 | $\frac{N-n_1}{2N} D \left\{ \underbrace{\left(1-\frac{n_1}{N}r\right)^k - \left(1-\frac{n_2}{N}r\right)^k}_{<0} \right\}$ | $\frac{n_1}{2N} \left\{ \underbrace{-k\left(1-\frac{n_1}{N}\right)r(D+d) + k\left(1-\frac{n_2}{N}\right)r(D+d)}_{>0} \right\}$ |
| 2 | $\frac{N-n_2}{2N} D \left\{ \underbrace{\left(1-\frac{n_2}{N}r\right)^k - \left(1-\frac{n_1}{N}r\right)^k}_{>0} \right\}$ | $\frac{n_2}{2N} \left\{ \underbrace{-k\left(1-\frac{n_2}{N}\right)r(D+d) + k\left(1-\frac{n_1}{N}\right)r(D+d)}_{<0} \right\}$ |

It also has an incentive to restrict travel by infected decision-makers in the riskier region ($I_1 > 0$). To understand this, note that the expected number of additional infections decreases if an infected individual is active in the riskier region, since the people in this region that this individual comes into contact with are more likely to already be infected. Therefore, travel by infected decision-makers in the riskier region also has a negative externality. These two incentives may lead to the intuitive, although insufficient, explanation of the proposition that when infectious diseases spread asymmetrically, travel to/from the riskier region should be discouraged.

However, $S_1$ and $I_2$ are negative, indicating that the government also has incentives to subsidize travel even when infectious diseases spread. Susceptible decision-makers from the riskier region (region 1) do not take into account the decrease in government expenditures associated with the reduced probability of infection. The government therefore has an incentive to make them internalize the *positive* externality of travel to the safer region, which is reflected by $S_1 < 0$. Additionally, there is a positive externality from travel by infected decision-makers from the safer region (region 2). The expected number of additional infections and the associated social costs can be reduced by moving this person to the riskier region. Therefore, $I_2$ is also negative. The bidirectional nature of the interregional travel market thus results in simultaneously both negative and positive externalities of travel and accordingly the government's incentives both to discourage ($S_2$

and $I_1$) and to encourage ($S_1$ and $I_2$) the movement of people.

Nevertheless, proposition 2 states that the optimal tax is *always* positive in this situation. The reason stems from the weights of each incentive, which correspond to the ratio of targeted individuals over the total population. First, the incentives to intervene for susceptible individuals ($S_1 < 0$ and $S_2 > 0$) are compared. Recall that the absolute values in curly braces are the same but have the opposite signs. Since $n_2 < n_1$ with the same population ($N_1 = N_2 = N$), there are more susceptible decision-makers in region 2 than in region 1 (i.e., $N - n_2 > N - n_1$). The government therefore places a greater weight on $S_2$, resulting in $S_1 + S_2 > 0$. Second, the weights of the interventions for infected individuals ($I_1 > 0$ and $I_2 < 0$) are compared. The absolute values in curly braces are again identical. The government places a greater weight on $I_1$ because $n_1 > n_2$. Therefore, $I_1 + I_2 > 0$. Combining these, the optimal tax is proven to be positive. Intuitively, because susceptible decision-makers tend to be more common in the safer region than in the riskier region and because infected individuals tend to be more common in the riskier region than in the safer region, the restriction of interregional travel is the optimal policy.

Similarly, $A^* > 0$ when $N_1 \neq N_2$, the other parameters ($n_i$, $r_i$, and $D_i$) are symmetric, and $\alpha = 0$. Specifically, suppose that $N_1 < N_2$, meaning that region 1 is riskier in the sense that the share of infected residents is higher than region 2. In this case, the signs of the components of $A^*$ are identical to those in the case of proposition 2: $S_1 < 0$, $S_2 > 0$, $I_1 > 0$, and $I_2 < 0$. Since susceptible decision-makers are more common in the safer region ($N_1 - n < N_2 - n$), the intervention for them ($S_2 > 0$) is weighted higher, that is, $S_1 + S_2 > 0$. Since the number of infected decision-makers is the same across regions ($n_1 = n_2$), the incentives of the interventions for infected residents fully cancel out, that is, $I_1 + I_2 = 0$.

It is obvious from Table 2 that $A^* = 0$ if either one of $r_i$ or $D_i$ is asymmetric. In summary, when $\alpha = 0$ and only one of the four parameters is asymmetric, then $A^* \geq 0$.

Interestingly, however, if more than one of the parameters is asymmetric, then a negative tax (i.e., subsidy) can be optimal. Before providing four examples as the proof, the result is summarized as a proposition and interpreted.

Proposition 3. When two parameters are asymmetric, $A^*$ could be negative.

This means that even when infectious diseases are widespread, a subsidy (not a tax) on travel could be optimal. At first glance, this result may appear counterintuitive. It stems from (i) the bidirectional nature of interregional travel and (ii) the impossibility of distinguishing susceptible and infected decision-makers. First, as Table 2 indicates, if one of $S_1$ and $S_2$ is positive, the other must be negative due to the bidirectionality of travel. Similarly, if one of $I_1$ and $I_2$ is positive, then the other is negative. Therefore, according to the relative weights, the optimal tax may be negative. Second, the impossibility of setting the tax differentially according to infectious status is another driver of this result. On the one hand, the government wants susceptible decision-makers to be active in the safer region. On the other hand, it is better for infected decision-makers to be active in the riskier region, where residents are more likely to already be infected and coming into contact with infected decision-makers causes fewer additional infections. Therefore, according to the weights, the sum of $S_1$ and $I_1$ and/or that of $S_2$ and $I_2$ may be negative.

It is easy to find examples in which the optimal tax is negative. Four of them are

Table 4
Case of example 1: $r_i > r_{-i}$ and $D_i > D_{-i}$

| | $S$ | $I$ |
|---|---|---|
| $i$ | $\frac{N-n}{2N} D_i \left\{ \underbrace{\left(1-\frac{n}{N}r_i\right)^k - \left(1-\frac{n}{N}r_{-i}\right)^k}_{<0} \right\}$ | $\frac{n}{2N}\left\{ \underbrace{-k\left(1-\frac{n}{N}\right)r_i(D_i+d) + k\left(1-\frac{n}{N}\right)r_{-i}(D_{-i}+d)}_{<0} \right\}$ |
| $-i$ | $\frac{N-n}{2N} D_{-i} \left\{ \underbrace{\left(1-\frac{n}{N}r_{-i}\right)^k - \left(1-\frac{n}{N}r_i\right)^k}_{>0} \right\}$ | $\frac{n}{2N}\left\{ \underbrace{-k\left(1-\frac{n}{N}\right)r_{-i}(D_{-i}+d) + k\left(1-\frac{n}{N}\right)r_i(D_i+d)}_{>0} \right\}$ |

presented in the remainder of this section. The first is a situation where both the probability of being infected by contact ($r_i$) and government expenditures per infection ($D_i$) are larger in one region than in another.

Example 1. When $n_i = n_{-i}, N_i = N_{-i}, r_i > r_{-i}, D_i > D_{-i}, and\ \alpha = 0,$ then $A^* < 0$.

Table 4 summarizes the components of $A^*$. The government has incentives to induce susceptible decision-makers to be active in the region with a lower probability of infection (region $-i$), which are reflected by $S_i < 0$ and $S_{-i} > 0$. The larger government expenditures in region $i$ mean that the social costs of an infection are higher for residents of region $i$ than those of region $-i$, resulting in $S_i + S_{-i} < 0$. The government also has incentives to induce infected decision-makers to be active in region $-i$, where both the probability of infecting others and government expenditures per infection are lower. Therefore, $I_i < 0$ and $I_{-i} > 0$. These are completely offset (i.e., $I_i + I_{-i} = 0$) because the number of infected decision-makers is same (i.e., $n_i = n_{-i}$).

The second example is the situation where the infection is more widespread in region $i$ and government expenditures per infection are sufficiently higher in the same region.

Example 2. When $n_i > n_{-i}, N_i = N_{-i}, r_i = r_{-i}, D_i > (D_{-i} + d)\frac{N-n_{-i}}{N-n_i} - d, and\ \alpha =$

Table 5

Case of example 2: $n_i > n_{-i}$ and $D_i > (D_{-i} + d)\frac{N-n_{-i}}{N-n_i} - d$

| | $S$ | $I$ |
|---|---|---|
| $i$ | $\frac{N-n_i}{2N} D_i \left\{ \underbrace{\left(1 - \frac{n_i}{N} r\right)^k - \left(1 - \frac{n_{-i}}{N} r\right)^k}_{<0} \right\}$ | $\frac{n_i}{2N} \left\{ \underbrace{-k\left(1 - \frac{n_i}{N}\right) r(D_i + d) + k\left(1 - \frac{n_{-i}}{N}\right) r(D_{-i} + d)}_{<0 \text{ if } D_i \text{ is sufficiently large}} \right\}$ |
| $-i$ | $\frac{N-n_{-i}}{2N} D_{-i} \left\{ \underbrace{\left(1 - \frac{n_{-i}}{N} r\right)^k - \left(1 - \frac{n_i}{N} r\right)^k}_{>0} \right\}$ | $\frac{n_{-i}}{2N} \left\{ \underbrace{-k\left(1 - \frac{n_{-i}}{N}\right) r(D_{-i} + d) + k\left(1 - \frac{n_i}{N}\right) r(D_i + d)}_{>0 \text{ if } D_i \text{ is sufficiently large}} \right\}$ |

$0,$ then $A^* < 0.$

Table 5 summarizes the components of $A^*$ in this situation. Since susceptible decision-makers should be kept away from the riskier region, $S_i < 0$ and $S_{-i} > 0$. The government believes that $S_i$ is more important than $S_{-i}$ due to the larger expenditures per infection in the region $i$. Therefore, $S_i + S_{-i} < 0$. The sufficiently larger expenditures per infection in region $i$ also indicate that it is better for infected decision-makers to be active in region $-i$ and thus that $I_i < 0$ and $I_{-i} > 0$. Because there are more targeted individuals for $I_i$, $I_i + I_{-i} < 0$.

The third situation is similar to example 2.

Example 3. When $n_i = n_{-i}, N_i < N_{-i}, r_i = r_{-i}, D_i > D_{-i}\frac{N_{-i}-n}{N_i-n}, and\ \alpha = 0,$ then $A^* <$

$0.$

Infection spreads more in region $i$ in the sense that the share of infected residents in the population $(n/N_i)$ is larger due to the smaller denominator, while it is larger because of the larger numerator in example 2. Additionally, government expenditures per infection $(D_i)$ are sufficiently larger in region $i$ than in region $-i$, as in example 2. Table 6 shows

Table 6

Case of example 3: $N_i < N_{-i}$ and $D_i > D_{-i}\frac{N_{-i}-n}{N_i-n}$

| | $S$ | $I$ |
|---|---|---|
| $i$ | $\frac{N_i - n}{N_i + N_{-i}} D_i \left\{ \underbrace{\left(1-\frac{n}{N_i}r\right)^k - \left(1-\frac{n}{N_{-i}}r\right)^k}_{<0} \right\}$ | $\frac{n}{N_i + N_{-i}} \left\{ \underbrace{-k\left(1-\frac{n}{N_i}\right)r(D_i+d) + k\left(1-\frac{n}{N_{-i}}\right)r(D_{-i}+d)}_{<0 \text{ if } D_i \text{ is sufficiently large}} \right\}$ |
| $-i$ | $\frac{N_{-i} - n}{N_i + N_{-i}} D_{-i} \left\{ \underbrace{\left(1-\frac{n}{N_{-i}}r\right)^k - \left(1-\frac{n}{N_i}r\right)^k}_{>0} \right\}$ | $\frac{n}{N_i + N_{-i}} \left\{ \underbrace{-k\left(1-\frac{n}{N_{-i}}\right)r(D_{-i}+d) + k\left(1-\frac{n}{N_i}\right)r(D_i+d)}_{>0 \text{ if } D_i \text{ is sufficiently large}} \right\}$ |

Table 7

Case of example 4: $N_i > N_{-i}$ and $r_i > r_j\frac{N_i}{N_{-i}}$

| | $S$ | $I$ |
|---|---|---|
| $i$ | $\frac{N_i - n}{N_i + N_{-i}} D \left\{ \underbrace{\left(1-\frac{n}{N_i}r_i\right)^k - \left(1-\frac{n}{N_{-i}}r_{-i}\right)^k}_{<0} \right\}$ | $\frac{n}{N_i + N_{-i}} \left\{ \underbrace{-k\left(1-\frac{n}{N_i}\right)r_i(D+d) + k\left(1-\frac{n}{N_{-i}}\right)r_{-i}(D+d)}_{<0 \text{ if } r_i \text{ is sufficiently large}} \right\}$ |
| $-i$ | $\frac{N_{-i} - n}{N_i + N_{-i}} D \left\{ \underbrace{\left(1-\frac{n}{N_{-i}}r_{-i}\right)^k - \left(1-\frac{n}{N_i}r_i\right)^k}_{>0} \right\}$ | $\frac{n}{N_i + N_{-i}} \left\{ \underbrace{-k\left(1-\frac{n}{N_{-i}}\right)r_{-i}(D+d) + k\left(1-\frac{n}{N_i}\right)r_i(D+d)}_{>0 \text{ if } r_i \text{ is sufficiently large}} \right\}$ |

the components of $A^*$. By the same logic as in example 2, $S_i + S_{-i} < 0$. The same number of infected decision-makers ($n_i = n_{-i}$) means $I_i + I_{-i} = 0$ as in example 1.

Examples 1-3 are all situations with an asymmetric $D_i$. The last example shows that the optimal tax could also be negative when $D_i$ is symmetric.

Example 4. When $n_i = n_{-i}, N_i > N_{-i}, r_i > r_{-i}\frac{N_i}{N_{-i}}, D_i = D_{-i}, and\ \alpha = 0,$ then $A^* < 0$.

This is a situation where the probability of being infected by contact with an infected person ($r_i$) is sufficiently larger in the region with a larger population. Table 7 describes $S_i$ and $I_i$ in the situation. Since susceptible decision-makers should be kept away from the riskier region (region $i$), $S_i < 0$ and $S_{-i} > 0$. The weight on $S_i$ is larger because of the larger population in region $i$, resulting in $S_i + S_{-i} < 0$. The incentives regarding infected decision-makers are completely canceled out ($I_i + I_{-i} = 0$) because the number

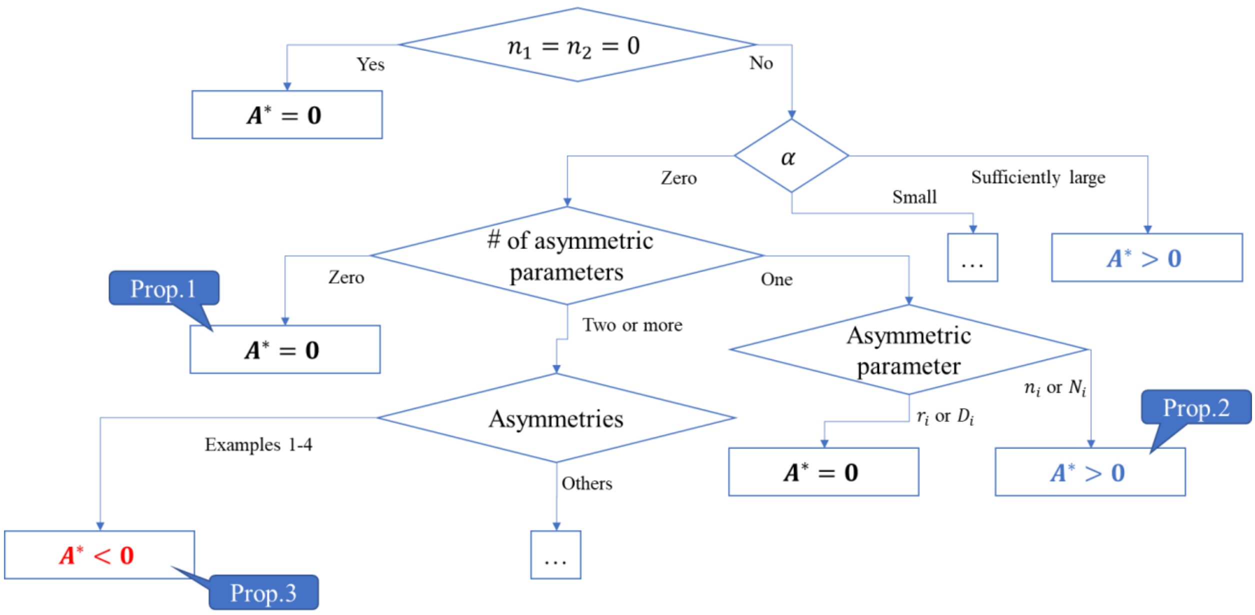



Figure 2
Summary of Theoretical Results

of infected residents is same ($n_i = n_{-i}$).

Figure 2 summarizes the results discussed in this section. In the model, the optimal tax is zero in the absence of infectious disease ($n_1 = n_2 = 0$). With infected residents in at least one region, if the increase in contacts during travel ($\alpha$) is sufficiently large, the optimal tax is positive to address the large negative externalities of travel. Focusing on situations where travel does not increase contacts ($\alpha = 0$), it is shown that $A^*$ could be zero, positive, or negative. If two regions are symmetric, $A^* = 0$ (proposition 1). If only one of the four parameters is asymmetric, then $A^* \geq 0$. In particular, when the number of infected decision-makers ($n_i$) is asymmetric, a positive $A^*$ to restrict travel is optimal (proposition 2). However, in more complicated situations where more than one parameter is asymmetric, it is easy to find examples in which $A^*$ is negative (proposition 3). The next section provides numerical examples to show that $A^*$ could be both positive and negative within a realistic range of parameter values.

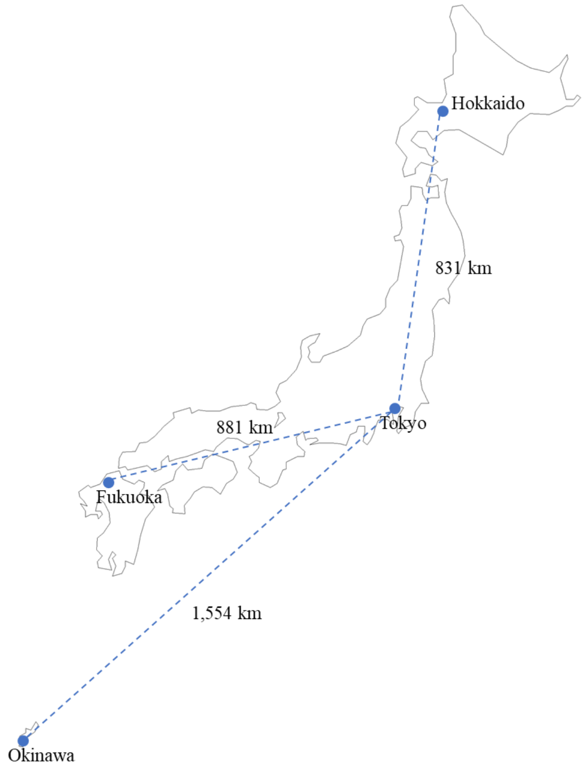



Figure 3
Location of Prefectures

# 4 Numerical Examples

This section provides numerical examples. Subsection 4.1 discusses the optimal tax under parameter values that conform to the situation in Japan in 2020. Subsection 4.2 investigates the sensitivity of the optimal tax to parameter values.

## *4.1* Situation of Japan in 2020

This subsection presents the optimal tax for six situations: three pairs of regions of Japan at two time points in 2020. The pairs of regions are Tokyo (region 1) and Hokkaido, Fukuoka, or Okinawa (region 2). Because the model supposes travel with a stay of several days, three major prefectures located far from Tokyo are selected (Figure 3). Hokkaido (831 kilometers from Tokyo) and Okinawa (1,554 kilometers) are located in the

Table 8

Data and Assumption to Set Parameter Values

| Parameter | Data | Assumption |
|---|---|---|
| $N_i$ | Population on October 1, 2019 from Statistics Bureau of Japan. | 1/60 of the population. |
| $n_i$ | The daily number of infectious cases from Ministry of Health, Labour, and Welfare. | 1/60 of the number. |
| $k$ | The number of close contacts for each infection case reported by Asahikawa City. The average is 4.5 as of February 15, 2021. | Five. |
| $r_i$ | The effective reproduction number calculated based on the daily number of infectious cases. | To be set to equate the expected additional infections in the model, $k(1 - n_i/N_i)r_i$ , to the effective reproduction number. |
| $\alpha$ | - | 0 or 0.5k. |
| $D_i$ | - | One million JPY. |
| $d$ | - | 0.3 million JPY. |

Note: The average of the last seven days is used for the number of infectious cases and the effective reproduction number to take into account day of the week.

northernmost and southernmost parts of Japan, respectively, and are popular tourist destinations. Fukuoka (881 kilometers) is the largest prefecture in Kyushu, the southern main island of Japan. The time points are July 22, 2020, when the travel promotion campaign in Japan began, and December 28, 2020, when the campaign stopped due to the spread of COVID-19.

The optimal tax depends on seven parameters: $N_i$, $n_i$, $k$, $r_i$, $\alpha$, $D_i$, and $d$. Table 8 summarizes the data source and assumptions used to set parameter values. The number of decision-makers who determine whether to travel ($N_i$) is set based on the population of each prefecture (the population estimates on October 1, 2019, provided by the Statistics Bureau of Japan). The decision-makers on a day are assumed to be one-sixtieth of the population. Accordingly, the number of infected decision-makers ($n_i$) is assumed to be one-sixtieth of the daily number of infectious cases.[7] The number of contacts of a decision-maker ($k$) is assumed to be five. This is set to be near the average number of close contacts of Asahikawa city, 4.48, as of January 29, 2021. Asahikawa is the second largest city in Hokkaido and a rare example in Japan that reports the number of close contacts for each infectious case. The probability that a susceptible individual becomes infected when coming into contact with an infected individual ($r_i$) is set to equate the expected number of additional infections caused by an infected person, $k(1-n_i/N_i)r_i$, to the data on the effective reproduction number of the region. The effective reproduction number is calculated based on the data on the daily number of infectious cases and the formula based on Jung, Akhmetzhanov, Mizumoto, and Nishiura (2020), as in Fujii and Nakata (2021). To account for day-of-the-week effects, the average for the last seven days is used in the calculations. Because of the lack of consensus on the extent of the increase in contacts during travel ($\alpha$), both $\alpha = 0$ and $0.5k$ are considered. Due to the lack of available data, $D_i$ and $d$ are assumed to be one million JPY (approximately 10 thousand USD) and 0.3 million JPY (three thousand USD), respectively. Subsection 4.2 addresses the robustness of the results to these assumptions.

Table 9 shows the data and parameter values. Tokyo has a population of 13.9 million and is the largest prefecture in Japan, which has a population of 126 million and 47 prefectures. Hokkaido, Fukuoka, and Okinawa are the eighth, ninth, and 25th largest prefectures, with populations of 5.3 million, 5.1 million, and 1.5 million, respectively. The number of infectious cases is the largest in Tokyo and larger on July 22 than on December 28 for all prefectures. The effective reproduction number varies across regions

[7] Even when the assumption on the share of decision-makers in the population is changed, the optimal tax calculated subsequently is unaffected.

Table 9

Parameter Values

| | Date | Data: Population (million) | Data: Infectious cases (daily) | Data: Effective reproduction number | Parameter: $N_i$ (thousand) | Parameter: $n_i$ | Parameter: $r_i$ | Reference indices: $n_i/N_i$ | Probability *not* to be infected: Stay | Travel to Tokyo: *α=0* | Travel to Tokyo: *α=0.5k* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| (Region 1) | | | | | | | | | | | |
| Tokyo | 7.22 | 13.9 | 242.9 | 1.25 | 232.0 | 4.05 | 0.25 | 0.000017 | 0.999978 | - | - |
| | 12.28 | 13.9 | 743.1 | 1.13 | 232.0 | 12.39 | 0.23 | 0.000053 | 0.999940 | - | - |
| (Region 2) | | | | | | | | | | | |
| Hokkaido | 7.22 | 5.3 | 8.1 | 2.23 | 87.5 | 0.14 | 0.45 | 0.000002 | 0.999997 | 0.999978 | 0.999967 |
| | 12.28 | 5.3 | 106.9 | 0.78 | 87.5 | 1.78 | 0.16 | 0.000020 | 0.999984 | 0.999940 | 0.999909 |
| Fukuoka | 7.22 | 5.1 | 26.4 | 1.65 | 85.1 | 0.44 | 0.33 | 0.000005 | 0.999991 | 0.999978 | 0.999967 |
| | 12.28 | 5.1 | 132.3 | 1.22 | 85.1 | 2.20 | 0.24 | 0.000026 | 0.999968 | 0.999940 | 0.999909 |
| Okinawa | 7.22 | 1.5 | 1.3 | 1.02 | 24.2 | 0.02 | 0.20 | 0.000001 | 0.999999 | 0.999978 | 0.999967 |
| | 12.28 | 1.5 | 33.0 | 1.09 | 24.2 | 0.55 | 0.22 | 0.000023 | 0.999975 | 0.999940 | 0.999909 |

Note: The number of infectious cases and the effective reproduction number are the average of the last seven days.

and days. The number exceeds one except for Hokkaido on December 28, meaning that Japan was in the expansion phase of COVID-19 on both days.

The probability of infection ($r_i$) is estimated to be 0.16-0.45. Note that this number should be interpreted with caution when the number of infectious cases is small because even a small change in the number of infectious cases results in substantial changes in the effective reproduction number and in turn the estimated probability of infection. Excluding the observations with relatively small numbers of infectious cases (Hokkaido, Fukuoka, and Okinawa on July 22), the probability of infection ranges from 0.16 to 0.25. Cheng et al. (2020) report that the probability of secondary clinical attack by an infected person in Taiwan is 0.7 percent with a 95 percent confidence interval of 0.4 percent to 1.0 percent, which is much smaller than the range in Table 9. One reason for the discrepancy is the difference in the definition of close contacts. Cheng et al. (2020) report that the number of close contacts per infected person is 27.61, which is much larger than the assumption of $k = 5$ based on the data for Asahikawa city in Hokkaido. If the number of close contacts is assumed to be 27.61, $r_i$ is estimated to be from 2.5 percent to 4.5 percent and becomes nearer to the reported number of Cheng et al. (2020). Additionally, $r_i$ is calculated based on the number of reported infectious cases, which includes asymptomatic infection cases and infections without close contacts, neither of which is reflected in the number of Cheng et al. (2020).

Table 9 also presents key indexes to understand the optimal tax. First, the share of infected individuals among decision-makers ($n_i/N_i$) is larger in Tokyo than in the other prefectures. However, it is small and at most 0.0053 percent. Second, due to this small share of infected residents, the probability that a susceptible person is *not* infected is nearly 100 percent in all situations. For example, it is 99.9997 percent for susceptible decision-makers in Hokkaido on July 22. If they travel to Tokyo, the probability decreases but remains at 99.9978 percent for $\alpha = 0$ and 99.9967 percent for $\alpha = 0.5k$. Thus, the probability depends little on whether they stay or travel. The difference is at most 0.0066 percent for Okinawa on December 28 with $\alpha = 0.5k$.

Table 10 shows the results. The upper and lower sections are for $\alpha = 0.5k$ and 0, respectively. Panels I and II present the breakdowns of $S_i$ and $I_i$. Panel I shows the externalities of travel. A positive value means that travel causes a negative externality and should be restricted by a tax. A negative value means a positive externality, which should be internalized by a subsidy. Because of the larger ratio of infected individuals ($n_i/N_i$) in Tokyo, travel by susceptible decision-makers in Tokyo has a positive externality and should be promoted by a subsidy ($S_1 < 0$). In contrast, travel by susceptible decision-makers in another region has a negative externality and should be restricted by a tax ($S_2 > 0$). If the number of contacts increases due to travel ($\alpha = 0.5k$), both $S_1$ and $S_2$ shift toward positive relative to the case of $\alpha = 0$. An important observation shown in Panel

Table 10
Results of Numerical Examples

| Region 2 | Date | I Externality per travel (thousand JPY) $S_1$ | $S_2$ | $I_1$ | $I_2$ | II Weight $S_1$ | $S_2$ | $I_1$ | $I_2$ | III I * II (JPY) $S_1$ | $S_2$ | $I_1$ | $I_2$ | IV Optimal tax (JPY) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\alpha = 0.5\ k$ | | | | | | | | | | | | | | |
| Hokkaido | 7.22 | **-0.017** | 0.029 | 2,717.5 | **-452.7** | 72.6% | 27.4% | 0.00127% | 0.00004% | **-12.1** | 8.0 | 34.4 | **-0.2** | 30.2 |
| | 12.28 | **-0.037** | 0.075 | 40.9 | 1,200.1 | 72.6% | 27.4% | 0.00388% | 0.00056% | **-26.7** | 20.5 | 1.6 | 6.7 | 2.1 |
| Fukuoka | 7.22 | **-0.009** | 0.024 | 1,586.7 | 301.2 | 73.2% | 26.8% | 0.00128% | 0.00014% | **-6.6** | 6.5 | 20.3 | 0.4 | 20.6 |
| | 12.28 | **-0.013** | 0.059 | 913.9 | 618.1 | 73.2% | 26.8% | 0.00391% | 0.00070% | **-9.4** | 15.8 | 35.7 | 4.3 | 46.4 |
| Okinawa | 7.22 | **-0.021** | 0.032 | 353.4 | 1,123.4 | 90.5% | 9.5% | 0.00158% | 0.00001% | **-18.6** | 3.0 | 5.6 | 0.1 | **-9.9** |
| | 12.28 | **-0.023** | 0.066 | 645.4 | 797.2 | 90.5% | 9.5% | 0.00483% | 0.00021% | **-21.3** | 6.2 | 31.2 | 1.7 | 17.9 |
| $\alpha = 0$ | | | | | | | | | | | | | | |
| Hokkaido | 7.22 | **-0.018** | 0.018 | 1,268.1 | **-1,268.1** | 72.6% | 27.4% | 0.00127% | 0.00004% | **-13.4** | 5.0 | 16.1 | **-0.5** | 7.2 |
| | 12.28 | **-0.045** | 0.045 | **-463.7** | 463.7 | 72.6% | 27.4% | 0.00388% | 0.00056% | **-32.4** | 12.2 | **-18.0** | 2.6 | **-35.6** |
| Fukuoka | 7.22 | **-0.013** | 0.013 | 514.2 | **-514.2** | 73.2% | 26.8% | 0.00128% | 0.00014% | **-9.8** | 3.6 | 6.6 | **-0.7** | **-0.3** |
| | 12.28 | **-0.029** | 0.029 | 118.3 | **-118.3** | 73.2% | 26.8% | 0.00391% | 0.00070% | **-21.0** | 7.7 | 4.6 | **-0.8** | **-9.5** |
| Okinawa | 7.22 | **-0.021** | 0.021 | **-308.0** | 308.0 | 90.5% | 9.5% | 0.00158% | 0.00001% | **-19.0** | 2.0 | **-4.9** | 0.0 | **-21.9** |
| | 12.28 | **-0.036** | 0.036 | **-60.7** | 60.7 | 90.5% | 9.5% | 0.00483% | 0.00021% | **-32.4** | 3.4 | **-2.9** | 0.1 | **-31.8** |

Note: Region 1 is Tokyo.

I is that the absolute values of the externality of travel of susceptible residents are small, with a maximum of 75 JPY (approximately 0.75 USD). This is because the probability that a susceptible individual becomes infected changes little regardless of whether the person stays or travels, as shown in Table 9.

In contrast, the externalities of travel by infected residents, which are represented by $I_1$ and $I_2$, are large, with a maximum of 2.7 million JPY (approximately 27 thousand USD). This is because the expected number of additional infections (or the effective reproduction number shown in Table 9) substantially differs across regions. In essence, the government has incentives to induce infected decision-makers to stay in or travel to the region with fewer additional infections. Both $I_1$ and $I_2$ shift toward positive in the case of $\alpha = 0.5k$ relative to the case of $\alpha = 0$. The large externality of an infected person indicates that if the government can identify infected residents, it should intervene in their travel decisions with a high rate of tax or subsidy. However, during the incubation period, it is difficult to identify them and thus impossible to set taxes or subsidies differentially for infected and susceptible residents. Therefore, the optimal tax is the weighted average of the externalities regarding infected and susceptible decision-makers, the weights of which are the number of targeted individuals, as shown in equation (1).

Panel II of Table 10 presents the weights. Since the share of susceptible residents is the largest in Tokyo, the weight of $S_1$ is the largest (72.6 percent to 90.5 percent). The second largest is the weight of $S_2$ (9.5 percent to 27.4 percent). The weights of the externalities of infected residents ($I_1$ and $I_2$) are very small, with a maximum of 0.00483 percent, because the share of infected residents in the population is small. Multiplying the size of externalities (Panel I) and the weights (Panel II), all of $S_i$ and $I_i$ are found to be on the order of only 10 JPY (roughly 0.1 USD) as shown in Panel III.

Panel IV of Table 10 shows the optimal tax, the sum of the components in Panel III. In both cases, $\alpha = 0.5k$ and $\alpha = 0$, the optimal tax could be both positive or negative, suggesting that a subsidy to promote travel may be optimal in reality. If $\alpha = 0.5k$, the optimal tax is positive in five of the six situations. It is negative only in the situation where region 2 is Okinawa on July 22. Since Okinawa on July 22 has a relatively low risk of infection due to the small $r_2$ and $n_2/N_2$, the positive externality of susceptible residents of Tokyo is large. In addition, its weight is large because of both the small population of Okinawa and the small number of infected cases at 7.22. If $\alpha = 0$, the optimal policy is a subsidy in five of the six cases. A tax is optimal only when region 2 is Hokkaido on July 22. Since the expected number of additional infections by an infected individual is large there due to the large $r_2$ and small $n_2/N_2$, the negative externality of infected travelers from Tokyo is large.

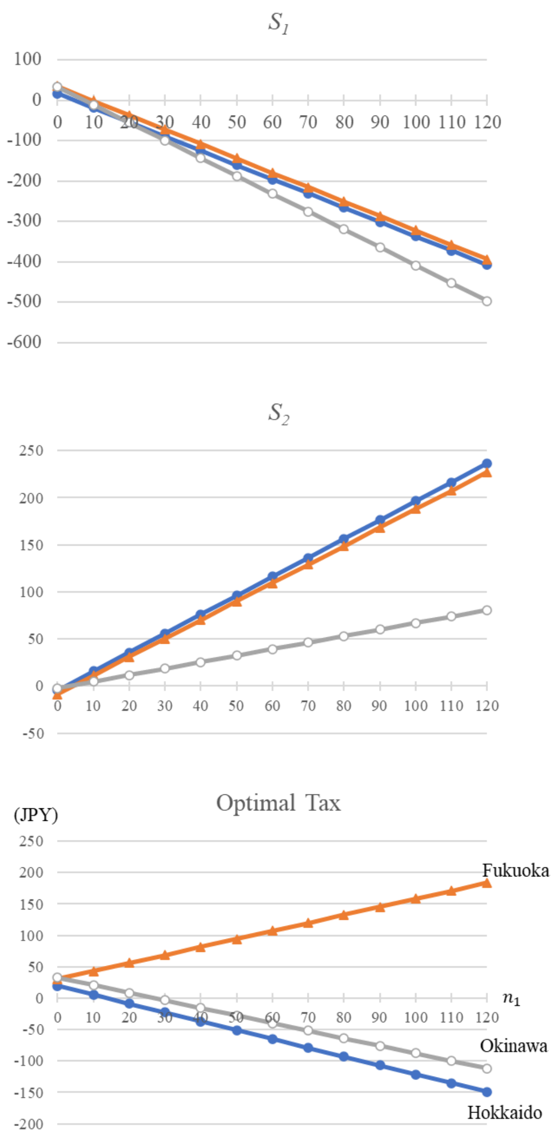
However, the absolute values of the optimal tax are small in all of the situations. The maximum is only 46 JPY (roughly 0.46 USD). The reasons are as follows. First, the externalities of susceptible individuals are small, as shown in Panel I. Second, although the externalities of infected individuals are large, their weights are very small, as shown in Panel II. Third, the positive and negative values of the four components shown in Panel III are partially cancelled out. These result in a low rate of the optimal tax or subsidy. This numerical example implies that although a subsidy to promote travel may be optimal in some realistic situations, a large subsidy cannot be supported for the situations analyzed in this subsection.

## *4.2* Sensitivity to parameter values

This subsection discusses how the optimal tax depends on parameters, focusing on $n_i$, $D_i$, and $d$. Throughout this subsection, the situations on December 28 and the case of $\alpha = 0.5k$ are considered.

First, we examine the sensitivity of the optimal tax to $n_i$. One reason for the low rates of the optimal tax calculated in the previous subsection is that the share of infected residents in the total population ($n_i/N_i$) is small. This results in both the almost 100 percent probabilities that a susceptible individual is not infected regardless of whether the individual travels and the small weights for the externalities regarding travel by infected residents. To examine how the rate becomes large when the $n_i$ of Tokyo increases, it is hypothetically increased to 120, which is approximately ten times as large as the actual value (12.39). If $n_1$ is 120, the share of infected residents in the total population is approximately 0.06 percent. This is not unrealistic. For example, the largest number of

Figure 4
Sensitivity to $n_1$



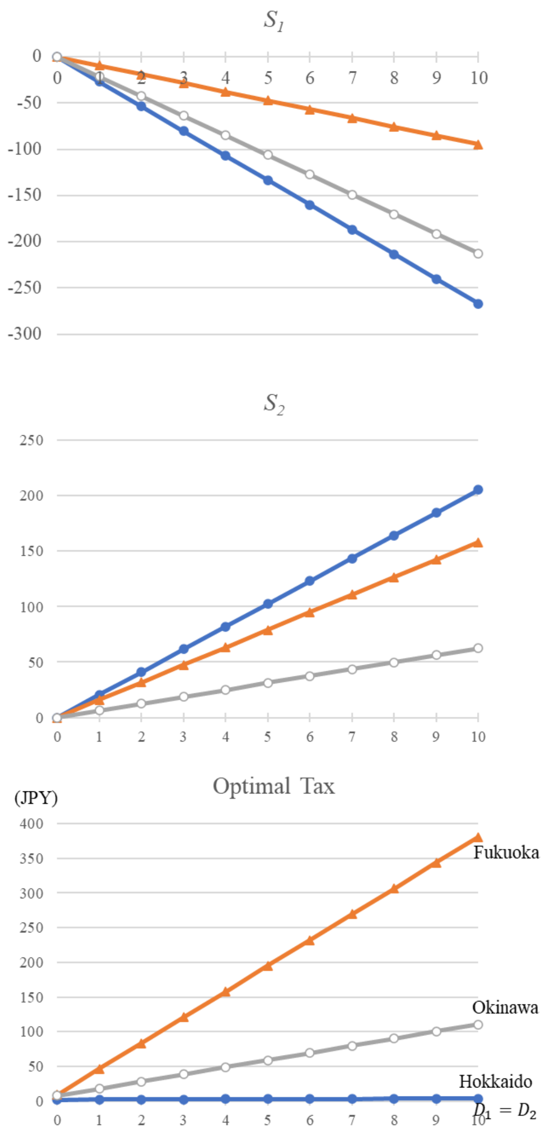

reported infection cases in New York city in 2020 was 12,697 on December 17 and accounted for 0.15 percent of its population.

Figure 4 shows the changes in the components of the optimal tax when $n_1$ increases. The top-left panel is for $S_1$, the term that captures the externality of travel by susceptible residents of Tokyo. As $n_1$ increases, $S_1$ decreases to encourage the susceptible to escape from Tokyo. The middle-left panel is for $S_2$ regarding susceptible residents of region 2. As $n_1$ increases, $S_2$ increases to persuade the susceptible to remain in the safer region. This effect is stronger when region 2 is Hokkaido and Fukuoka than when it is Okinawa because of their larger population and accordingly larger weights of $S_2$. The top-right panel is for $I_1$ regarding infected residents of Tokyo. An increase in $n_1$ increases $I_1$ simply because its weight, $n_1/(N_1 + N_2)$, increases. For the case when region 2 is Fukuoka and Okinawa, the negative externality per travel is larger than that of Hokkaido (see panel I of Table 10) due to the larger probability of infection ($r_i$). The middle-right panel shows that $I_2$, the term for infected residents of region 2, is almost unchanged but decreases very slightly.

The bottom-left panel is for the optimal tax, the total of the four components. Interestingly, when $n_1$ increases, while the optimal tax increases for travel to/from Fukuoka, it decreases for travel to/from Hokkaido or Okinawa. For the Fukuoka market, the tax-increasing effects of $n_1$ through $S_2$ and $I_1$ are both larger. In contrast, for the Hokkaido and Okinawa markets, because either one of the effects through $S_2$ or $I_1$ is small, the tax-decreasing effects through $S_1$ dominate the sum of them. This result implies that even when infectious diseases spread more in the epicenter, not only a tax but also a subsidy on interregional travel may be optimal depending on the situation of the paired region. However, the absolute values of the tax or subsidy remain small in all cases analyzed here. Even when $n_1 = 120$, they are 100-200 JPY (roughly 1-2 USD). This is because the tax-increasing and tax-decreasing effects are partially cancelled out.

Second, the sensitivity of the optimal tax to government expenditure per infection ($D_i$) is examined. It consists of, for example, the costs of medical treatment and administration regarding infection control, and it is difficult to obtain comprehensive data on these aspects. In the baseline case in Subsection 4.1, the total is assumed to be one million JPY

Figure 5
Sensitivity to $D_1 = D_2$

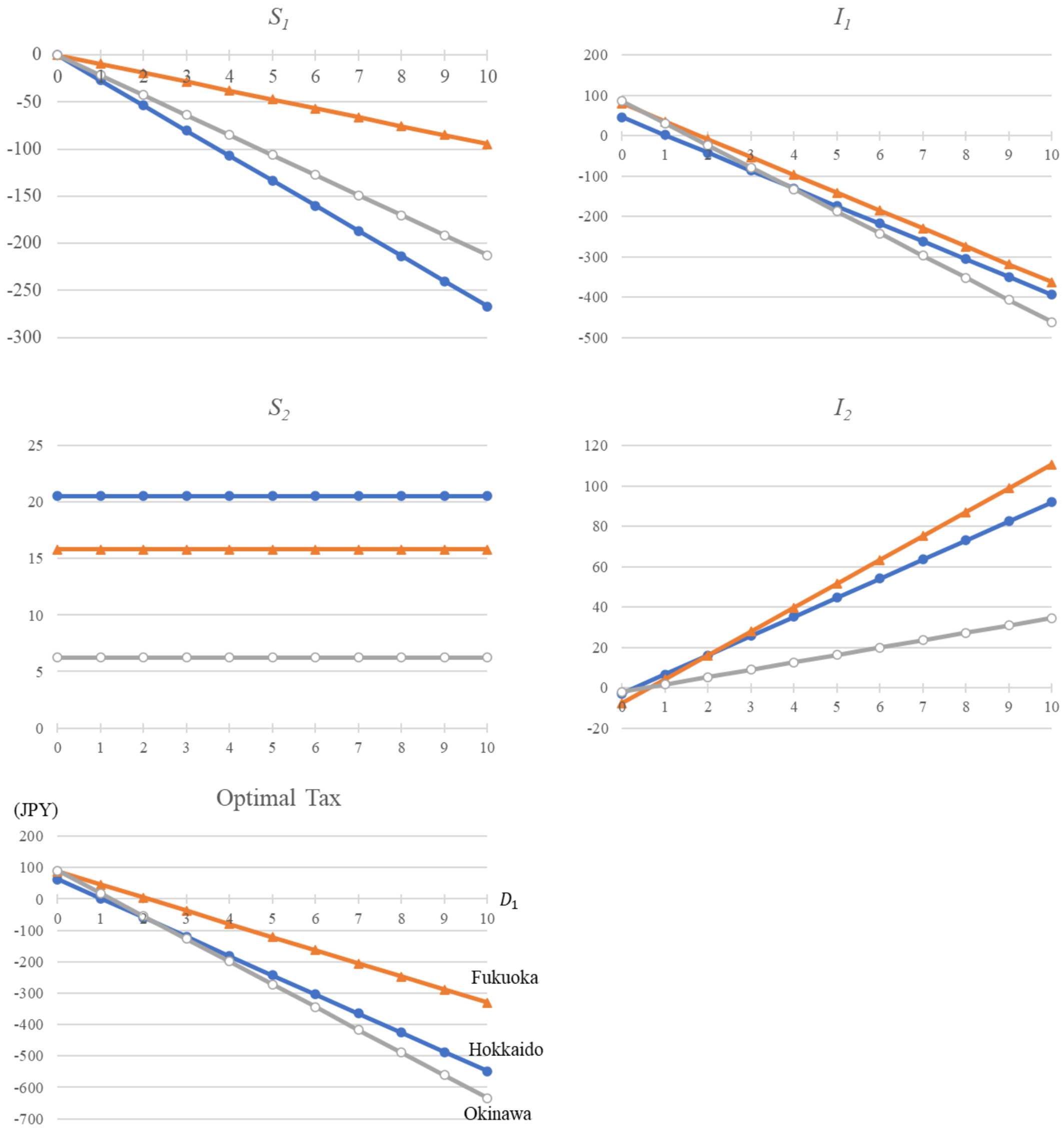



(approximately 10 thousand USD) for all situations.

To check the robustness of the assumption of $D_i$, its value is increased to ten times the baseline. Figure 5 shows the result. When $D_1$ and $D_2$ increase simultaneously, the components of the optimal tax are simply amplified. Accordingly, when they are increased tenfold, the optimal tax is also increased nearly tenfold.

Thus far, the government expenditure per infection, $D_i$, has been assumed to be the same in all regions. However, it may be larger in, for example, a region with higher wages

Figure 6
Sensitivity to $D_1$




or a region with more load applied to the medical system. Thus, the case in which only the expenditures of Tokyo are increased to ten times the baseline, while those of the other regions are unchanged, is examined. Figure 6 shows the result. The bottom-left panel shows that as $D_1$ increases, the optimal tax decreases. When $D_1$ becomes large, susceptible residents of Tokyo should be strongly encouraged to escape to a safer region ($S_1 < 0$), and infected residents of Tokyo also should be encouraged to travel to the other region to avoid spreading infection in Tokyo ($I_1 < 0$). Although infected residents of the other region should be kept away from Tokyo ($I_2 > 0$), the effects through $S_1$ and $I_1$ dominate it because of the large population of Tokyo. These results imply that the optimal tax is sensitive to the level and asymmetry of the government expenditure parameter $D_i$ and that it is important to set its values as exactly as possible.

Third and finally, we discuss the sensitivity to the assumption on the private damage of infection, $d$. In the baseline, it is assumed to be 0.3 million JPY (approximately 30 thousand USD), which is equivalent to 30 percent of government expenditures. Here, it is increased to ten times the baseline.

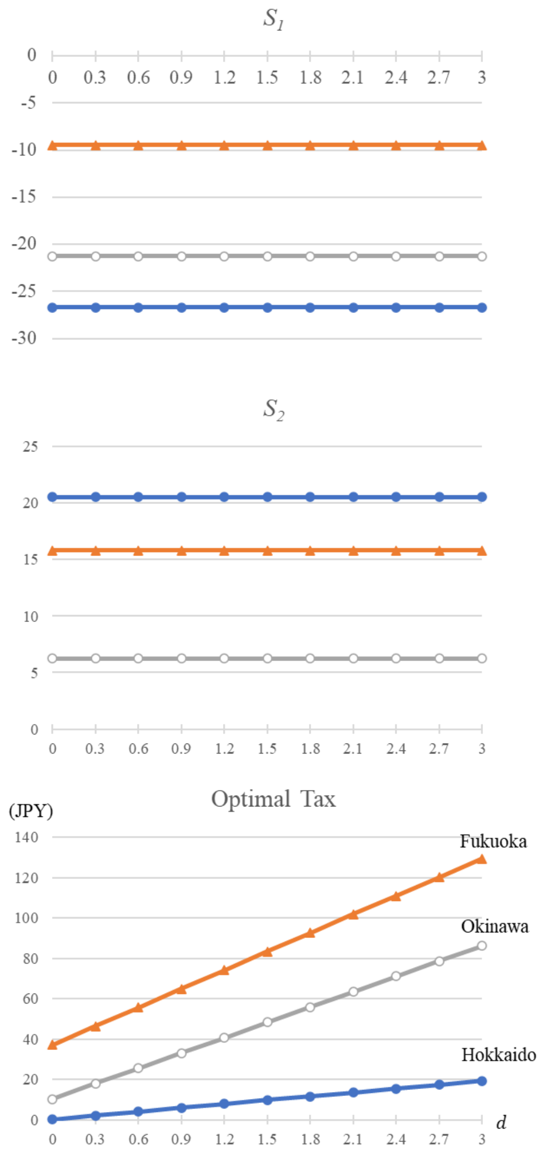
Figure 7 displays the result. Since susceptible residents fully internalize private damage, $S_1$ and $S_2$ do not depend on its amount. However, the greater the damage of infection is, the larger the negative externality of infected residents' spreading infection. Therefore, as $d$ increases, the terms that capture the negative externalities, $I_1$ and $I_2$, become large. However, because the weights of $I_1$ and $I_2$ are small due to the small share of infected individuals, the rate of the optimal tax remains small: 20-130 JPY (roughly 0.2-1.3 USD) even when the private cost is assumed to be ten times the baseline. This result implies that although the data on $d$ may be difficult to obtain, the optimal tax is not seriously affected by the value assumed for it.

# 5 Conclusion

This study theoretically investigated the externality of interregional travel with infectious diseases. Developing a two-region model with infectious diseases, this study considered the optimal tax or subsidy on interregional travel.

The results revealed that the optimal tax could be both positive and negative (i.e., a

Figure 7
Sensitivity to $d$




subsidy) depending on the asymmetry of the regions. The drivers of this result are (i) the bidirectional nature of the interregional travel market and (ii) the difficulty of distinguishing infected (but not symptomatic) residents from susceptible residents. Numerical examples, where the baseline parameter values are set in line with the situation of Japan in 2020, showed that a subsidy on travel may indeed be optimal in some realistic cases. However, the numerical results also suggested that the optimal subsidy is at most on the order of 10 JPY (approximately 0.1 USD) and therefore did not support offering large subsidies, as were provided in the `Go To Travel' campaign in Japan.

The results imply that it is not an easy question to answer how the government should intervene in interregional travel in the presence of infectious diseases. It is *not* always optimal to restrict travel even when infectious diseases spread. Additionally, whether a traveler comes into contact with more people when traveling than when staying in the place of residence is *not* the only determining factor of the optimal intervention. Rather, the intervention policy should be set by taking into account regional asymmetries, such as the number of infected residents, the population, the probability of transmission, and government expenditures per infection. This implication can be applicable not only for interregional travel within a country but also for international travel.

Note that this argument is subject to the presumption that the infectious diseases in a region cannot be fully contained in a short period. If possible, the strict restriction of interregional movement to achieve eradication of the virus may be socially optimal.

A limitation of this study is that it focuses on policy intervention in interregional movement and does not consider policies to reduce the probability of infection transmission within a region, such as stay-at-home orders and closing restaurants. The restriction of interregional movement may be more effective when combined with such intraregional measures. The optimal combination of them remains a question for future research. However, the insights obtained from this study could serve as a foundation for such research.

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