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Political Conflict and Angry Consumers: Evaluating the Regional Impacts of a Consumer Boycott on Travel Services Trade

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# Political Conflict and Angry Consumers: Evaluating the Regional Impacts of a Consumer Boycott on Travel Services Trade\*

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#### Abstract

Political conflict between nations sometimes leads to consumer boycotts. We examine the regional impacts of bilateral boycott activity by investigating the 2019 Korean consumer boycott of travel to Japan. Employing triple- and double-differences designs, we find that the impact of the boycott is large and regionally heterogeneous. Japanese prefectures with high (i.e., 75th percentile) pre-boycott dependency on visitors from Korea suffer bilateral export losses of 56.9 to 60.9 percent and aggregate export losses of 10.5 to 13.3 percent. Prefectures with low (i.e., 25th percentile) Korea dependency experience bilateral losses of 47.8 to 49.7 percent and aggregate losses of 3.3 to 4.2 percent.

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### 1 Introduction

Political conflict between nations often impacts international trade through official trade policy. Recent examples include several rounds of tariff escalation between the US and China in 2018 and 2019, the effects of which have been intensively investigated in the literature (e.g., Amiti, Redding, and Weinstein, 2019, Head and Mayer, 2019, and Fajgelbaum, Goldberg, Kennedy, and Khandelwal, 2020). When trade policy is used as a tool of diplomacy, planned changes in trade barriers are often announced in advance for administrative reasons (i.e., to provide time for customs officials to make necessary changes) and to create a window for further negotiation that might result in postponement or changes in announced barriers. However, when political conflict leads to calls for a consumer boycott directed at a trade partner, the effects can be immediate and therefore harder to evade (e.g., by stockpiling prior to a tariff increase). In addition, the effects of a boycott may be more unpredictable than trade policy effects since the popularity and longevity of the boycott, along with the pathway to alleviate it, are more uncertain. These features of consumer boycotts make them unique "unofficial" outcomes of political conflict and deserving of research attention.

A consumer boycott on imported products can be interpreted as another form of import restriction and therefore may have significantly negative effects on bilateral trade. For example, Heilmann (2016) examined the impact of several boycotts such as the boycott of Danish goods by Muslim countries following the Muhammad Comic Crisis in 2005/2006 and the Chinese boycott of Japanese goods in response to the Senkaku/Diaoyu Island conflict in 2012. He found an average one-year import disruption to boycotting countries of 18.8 percent in the case involving Denmark and 2.7 percent for that involving Japan. In contrast, the reduction in total exports of the boycotted country was small in all boycott cases (e.g., 0.4 percent for Denmark and 0.5 percent for Japan). Similarly, Heilmann (2019) focused on the effects of the same Muhmmad Comic Crisis on Danish service exports. He found that service exports in general and especially exports of travel services from Denmark to the Muslim countries were significantly disrupted in the aftermath of the crisis. Yu, McManus, Yen and Li (2020) provide further evidence of the vulnerability of travel services trade to consumer boycotts by using seven Chinese boycott cases to estimate that Chinese visitors to boycotted countries were 36.2 percent below their expected level 12 months after the boycott event.<sup>2</sup>

While these previous studies present important findings, they implicitly assumed that the impacts were homogenous across regions within a boycotted country or did not explicitly consider the heterogenous impacts across regions. There is another strand of research that examined the effects of trade liberalization at the regional level. After the pioneering study by Topalova (2007), which examined the effects of a trade shock on local labor markets in India,

<sup>&</sup>lt;sup>1</sup>For example, see Bowen and Kolb (2020) for a detailed timeline of President Trump's tariff announcements followed by announcements of country-specific exemptions (e.g., involving steel and aluminum tariffs) or changes to product coverage (e.g., involving China-specific tariffs) in 2018 and 2019.

<sup>&</sup>lt;sup>2</sup>Related literature on consumer boycotts includes Ashenfelter, Ciccarella and Shatz (2007), Chavis and Leslie (2009), Davis and Meunier (2011), Clerides, Davis, and Michis (2015) and Pandya and Venkatesan (2016). The relationships between political/cultural conflict and international economic exchange also are examined in Guiso, Sapienza and Zingales (2009), Fuchs and Klann (2013), Fisman, Hamao and Wang (2014), Li, Jian, Tian and Zhao (2021) and Zhou, Zhang and Zhou (2021). Heilmann (2016), Yu et al. (2020) and Zhou et al. (2021) provide excellent literature reviews on these issues.

several studies focused on the effects of trade liberalization on local labor markets.<sup>3</sup> These studies found that some regions have significantly larger negative effects than other regions due to import competition shocks. Recent studies of the United States-China trade war initiated in 2018 also suggest regional differences within the United States due to shocks transmitted through three trade war channels—import protection, import-using and foreign retaliation.<sup>4</sup> These studies suggest that the impact of a consumer boycott also could be heterogeneous across regions within a boycotted country.

In this connection, a recent study by Caselli, Koren, Lisicky and Tenreyro (2020) assessed the importance of cross-country diversification, based on a quantitative trade model. One of their findings is that international trade leads to lower income volatility because countries can diversify their sources of demand and supply across countries. This "diversification story" suggests that higher dependency on exports to a particular country can make a county more vulnerable to trade shocks. Applying this logic to the regional level means that the impact of a consumer boycott could be more severe in regions with higher dependency on exports to the boycotting country.

Based on this background, this paper investigates the regional impact of consumer boycott activity. A main contribution of this paper is to incorporate a local market perspective in analyzing the effect of a political conflict on trade. More specifically, we investigate the recent Korean consumer boycott activity from July 2019 in response to Japan's restrictions on exports of semiconductor materials and display panels considered vital to Korea's technology industry. As we will discuss in Section 2, this consumer boycott was unanticipated and plausibly exogenous to unobserved trade-related confounding effects, which helps us to identify the causal relationship between the consumer boycott and trade. The boycott activity spread not only to the purchase of Japanese goods but also to that of services: many Koreans stopped traveling to Japan. Decreases in travel to Japan mean decreases in Japan's exports of tourism services. This issue is important from a current policy perspective because increasing the number of inbound tourists is one of the essential strategies for spreading growth to regional economies under Abenomics (The Government of Japan, 2017).

This paper focuses on the exports of accommodation services from Japan. We measure exports by the number of foreign visitors, which is defined as the number of people who reside in countries other than Japan times the number of nights stayed in Japan. This means that foreign nationals who live in Japan are excluded while Japanese nationals who live outside of

<sup>&</sup>lt;sup>3</sup>See, for example, Topalova (2010) for the case of India; Autor, Dorn, and Hanson (2013) and Hakobyan and McLaren (2016) for the United States; Kovak (2013) for Brazil; and Taniguchi (2019) for Japan.

<sup>&</sup>lt;sup>4</sup>Fajgelbaum et al. (2020) and Caliendo and Parro (2021) develop models to simulate changes in real wages while Waugh (2019) examines the trade war's impacts on consumption patterns. Fajgelbaum and Khandelwal (2021) provide an excellent review of the studies on this recent trade war. Note that consumer boycott effects can be included within the foreign retaliation channel which focuses on changes in export volumes and prices.

<sup>&</sup>lt;sup>5</sup>Our focus is slightly different from that of the studies on local labor markets mentioned above. While these previous studies exploited the regional variations of trade shocks on regional economic outcomes (e.g., employment), our study exploits the regional variations of a trade shock due to political conflict on region-level trade itself.

<sup>&</sup>lt;sup>6</sup>For ease of exposition, "Korea" is used to refer to the Republic of Korea (i.e., South Korea) throughout the paper.

<sup>&</sup>lt;sup>7</sup>This boycott activity was also widely discussed in the media. See, for example, Stangarone (2020).

<sup>&</sup>lt;sup>8</sup>In fact, one analyst considers the growth in inbound tourism to be "the most tangible success story of Abenomics" (Koll, 2018, p. 1).

Japan are included if they use accommodation services while visiting Japan. Figure 1 shows the changes in the number of visitors from foreign countries in Japan on a monthly basis. Compared with visitors from China and the United States, those from Korea dropped sharply from July 2019, exactly when the boycott started. Figure 1 also indicates seasonality differences across countries. For example, visitors from China and Korea tend to increase in winter months (e.g., January and February) whereas visitors from the United States tend to increase in spring and summer months (e.g., May and June).

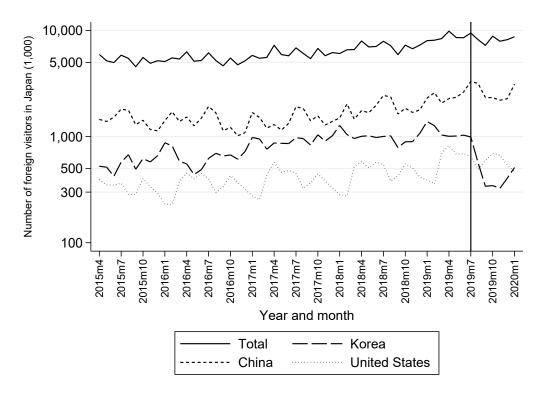


Figure 1: Number of Foreign Visitors in Japan

Notes: Total number of foreign visitors indicates the total number of people who reside outside of Japan times the number of nights stayed in Japan (unit: 1,000 person-nights).

Source: Japan Tourism Agency (2020) Overnight Travel Statistics Survey.

Note that the accommodation services market is locally segmented. Even though foreign visitors can move across prefectures in Japan, they are not able to import (i.e., consume) accommodation services in prefecture i from another prefecture. An advantage of focusing on this conflict is that the information on the number of foreign visitors is available at the prefecturementh level in Japan. This means that we can capture the trade volume (i.e., quantity) of

<sup>&</sup>lt;sup>9</sup>Total visitors include visitors whose information on resident countries is not available. Section 3 provides a more detailed explanation of the data.

<sup>&</sup>lt;sup>10</sup>One may be concerned that this sharp drop came from a demand shock in Korea, rather than from the boycott. For example, due to a demand shock, Korean people stopped traveling abroad, not only to Japan but also to other countries. We examine this alternative hypothesis in Section 6.

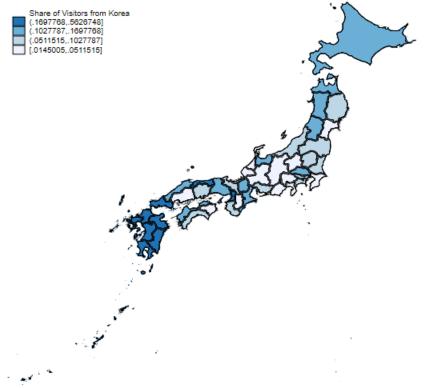
<sup>&</sup>lt;sup>11</sup> Figure 1 also indicates declines in visitors from Korea from about April to June 2016. This may be due to the 2016 Kumamoto earthquakes on April 14th and 16th that caused severe damage in Kumamoto and Oita prefectures. This caused some fluctuation in arrivals from Korea to Japan (OECD, 2018, p.210).

<sup>&</sup>lt;sup>12</sup>Japan consists of 47 administrative prefectures. In this paper, following Taniguchi (2019), we define the local market at the prefecture level.

services exports at the prefecture and month level.

Figure 2 presents each prefecture's dependency ratio on visitors from Korea, which is defined as the average share of visitors from Korea to total visitors from foreign countries between April 2015 and June 2019. We highlight two main findings. First, the dependency ratio shows significant differences across prefectures in Japan. The ratio ranges from 1.5 percent to 56.3 percent. Second, the ratios tend to be large in the Western part of Japan, which may reflect this region's closer proximity to Korea.<sup>13</sup>

Figure 2: Average Share of Visitors from Korea between April 2015 and June 2019, by Prefecture in Japan



Notes: A darker color means a larger Korean visitor dependency. Japanese map data are obtained from https://gadm.org/

Source: Japan Tourism Agency (2020) Overnight Travel Statistics Survey.

Using the prefecture-month foreign visitor data between April 2015 and January 2020, we employ triple-differences (i.e., difference-in-difference-in-differences, DDD) and double-differences (i.e., difference-in-differences, DID) designs to estimate the impact of the boycott. We find that the impact of the consumer boycott is heterogeneous across prefectures within Japan, which is in line with the diversification story. For prefectures with high pre-boycott dependency on visitors from Korea, the negative impact on exports of accommodation services to Korea is about 9 to 11 percentage points larger than it is for prefectures with low dependency, with export losses of 56.9 to 60.9 percent and 47.8 to 49.7 percent, respectively. These negative impacts are not only disproportionate across prefectures but also too large to be offset by in-

<sup>&</sup>lt;sup>13</sup>In addition to air travel, ferry service operates between two ports in Korea (i.e., Busan and Donghae) and five ports in Japan, of which four are in Western Japan (i.e., Hakata, Sakaiminato, Shimonoseki, and Tsushima).

creases in exports to other countries. As a result, Japanese prefectures had net adverse effects from the boycott, with a 10.5 to 13.3 percent decline in total exports of accommodation services for high Korea dependency prefectures and a corresponding decline of 3.3 to 4.2 percent for low Korea dependency prefectures. These ranges of boycott effects summarize our results in using two estimation models and two sample periods to identify estimated bands for the boycott effects that are reassuringly narrow for a specific quartile prefecture, heterogeneous across prefectures and robust to the exclusion of outliers. Our main message holds even when we use an alternative measure of diversification.

To explain the boycott's disproportionate effects on exports to Korea across prefectures, we examine the purpose of travel for visitors from Korea to Japan's prefectures using entry and exit survey data of foreign visitors collected by the Japan Tourism Agency. We find that prefectures with high pre-boycott dependency on visitors from Korea also tend to disproportionately attract tourists rather than non-tourist travelers from Korea. While we cannot formally test the hypothesis that the consumer boycott impacted leisure travel more than non-leisure travel due to data limitations, our results are consistent with this hypothesis. These results also are consistent with the finding of stronger boycott effects for consumer goods than for intermediate inputs or capital goods in the Muhammad Comic Crisis case (Heilmann, 2016). By examining the distinction between tourists and non-tourist visitors in the boycott effects, we contribute to the trade diversity literature by adding another dimension of diversity, type of buyer (i.e., traveler), to the conventional dimension of diversity by countries of origin or destination. Our results suggest that prefectures with more diverse visitors by country of origin and by traveler type (e.g., tourist, business traveler) may experience smaller impacts from consumer boycotts.

The paper is organized as follows. The next section describes the background of the political conflict between Japan and Korea in 2019. Section 3 introduces the main data used in our analysis. Sections 4 and 5 present the methodology and results of the empirical analyses at the disaggregate and aggregate levels, respectively. Section 6 presents robustness checks and discusses the interpretations and implications of the results. Section 7 includes our conclusions.

## 2 Political Conflict between Japan and Korea in 2019

Some historical context is necessary in order to understand the 2019 political conflict between Japan and Korea. Japan annexed Korea in 1910 and ruled the country for 35 years. During WWII, many Koreans were forced to work as slave laborers for Japanese companies and as sex slaves for Japanese soldiers. Korea was liberated in 1945 with Japan's defeat in the war, but diplomatic relations between the two countries were not normalized until 1965. The normalization treaty included a declaration that the compensation matter was settled by a payment of

<sup>&</sup>lt;sup>14</sup>A possible interpretation is that places with a large dependence on Korean tourists could be the ones with the highest name recognition in Korea, and subsequently suffer the most in response to the boycott. Prior studies like Pandya and Venkatesan (2016) and Heilmann (2016) have highlighted that boycotts are concentrated in products with high brand recognition.

<sup>&</sup>lt;sup>15</sup>Diversity by buyer type or buyer purpose of travel differs somewhat from Heilmann's (2016) separation of goods by product type. Accommodation services can be considered a "dual use" service, sold as a final consumer service to tourists and as an intermediate input service to business travelers.

USD 800 million in grants and soft loans from the Japanese government to the Korean government. The lack of victims' compensation or legal recourse in the treaty prompted mass protests and the imposition of martial law in Korea. President Park Chung-hee used the compensation money to fund economic development projects not to compensate victims of forced labor or sexual slavery under Japanese rule. Relations between the two countries oscillated between friendly and contentious over the ensuing five decades.<sup>16</sup>

In the fall of 2018, the Korean Supreme Court ruled in favor of Korean forced labor plaintiffs seeking compensation from Japanese firms. These firms, Mitsubishi Heavy Industries, Nippon Steel, Sumitomo Metal Corporation, and Nachi Fujikoshi, refused to pay damages citing the 1965 treaty. In January, 2019, a Korean court ruled that some of Nippon Steel's equity holdings in a joint venture company in Korea could be seized to cover the payments due. This prompted fears in Japan that other Japanese assets in Korea could be subject to seizure in the future as other court cases regarding forced labor compensation work their way through Korea's court system.

On July 4, 2019, the Japanese government dropped Korea from its "white list" of countries that receive preferential treatment for export licensing. This meant that Korea could no longer count on receiving automatic approval of purchases of chemicals and related products (e.g., display panels) that have dual commercial and military uses. Tokyo officials stated that this step was not retaliatory but rather due to national security concerns regarding suspicion that the chemicals were being transshipped from (South) Korea to North Korea. Of particular concern in Korea was continued access to three chemicals (i.e., hydrogen flouride, fluorinated polyimide, and resist polymers) needed to make semiconductors, Korea's top export industry. The perceived threat to Korea's vital industry led to consumer boycott activities in Korea against purchases of Japanese products and services, including travel to Japan, from early July 2019.

In August, 2019, President Moon Jae-in announced that he would drop Japan from Korea's "white list" and terminate the intelligence-sharing pact between the two countries that was set to expire in November, 2019. He also initiated a WTO case against Japan in September, 2019. Japan took some steps to reduce bilateral tensions by issuing its first export license for one of the restricted chemicals in August and approving of at least one shipment of each chemical by October, 2019. In November, 2019, Korea announced that it would stay in and extend the intelligence-sharing pact with Japan provided positive progress was being made in their bilateral dispute. Korea also suspended the WTO case against Japan in November, 2019, but then indicated in early June, 2020, that it would reopen the WTO case due to a lack of progress in the bilateral dispute.<sup>17</sup>

For the purposes of our study, the shock to Japan's economy caused by Korea's consumer boycott of Japanese goods and services can be considered an exogenous event. Japan's Prime Minister Shinzo Abe sought to put pressure on Korea's President Moon Jae-in regarding the court-ordered reparations so he introduced new export controls on chemicals of vital interest to Korea's top exporting industry, but these chemicals were a long-standing security concern for

<sup>&</sup>lt;sup>16</sup>See Lind (2019) for further details.

<sup>&</sup>lt;sup>17</sup>The slight easing of tensions from the Korean government's November, 2019, announcements may help to explain the small upturn in Korean travel to Japan at the end of our sample period as shown in Figure 1.

Japan (Obe and Kim, 2019). It seems unlikely that the Japanese government could anticipate that the export control announcement would ignite public outrage in Korea and many angry participants in the consumer boycott of Japanese exports. The suddenness and magnitude of the consumer boycott shock is illustrated by showing year-on-year changes in monthly visitors from Korea in Figure 3. The boycott-led drop in visitors is much stronger than those following recent earthquake disasters in Japan, including the Great East Japan Earthquake of March 11, 2011.

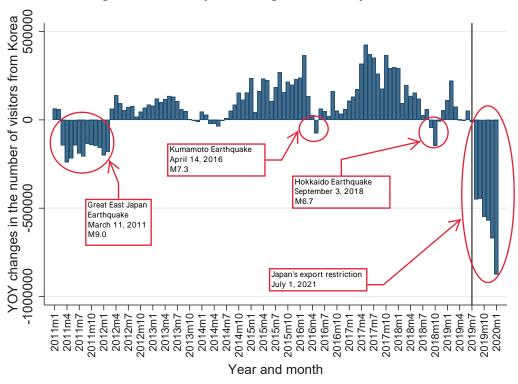


Figure 3: Year-on-year Changes in Monthly Visitors from Korea

Notes: Total number of foreign visitors indicates the total number of people who reside outside of Japan times the number of nights stayed in Japan (unit: 1,000 person-nights).

Source: Japan Tourism Agency (2020) Overnight Travel Statistics Survey.

#### 3 Data

#### 3.1 Source

In this paper, we focus on Japan's exports of accommodation services to visitors from foreign countries. <sup>18</sup> Our main outcome variable is exports from prefecture i in Japan to trading partners j at time t at monthly frequency,  $Y_{ijt}$ . We measure exports by the number of visitors from country j to prefecture i in Japan at time t (year-month).

The main source of the data is the Overnight Travel Statistics Survey (Shukuhaku Ryokou Toukei

<sup>&</sup>lt;sup>18</sup>Trade in tourism services is a type of services trade. It is classified as mode 2 (consumption abroad) in the General Agreement on Trade in Services.

Chousa in Japanese) by the Japan Tourism Agency, the Government of Japan. This survey is conducted for establishments in the accommodation services industry on a monthly basis. The survey covers all establishments that have greater than or equal to 10 workers and for randomly sampled establishments that have less than 10 workers. The survey collects information such as the location of the establishments and the number of foreign visitors, by their country of residence and by their purpose of travel. As mentioned in Section 1, because foreign visitors are defined as visitors who reside in countries other than Japan, foreign national visitors who live in Japan are excluded whereas Japanese national visitors who live outside of Japan are included if they use accommodation services while visiting Japan.

While the use of this dataset has several advantages, it also has some limitations. First, some of the information, such as the number of visitors by country of residence, is available only for establishments with greater than or equal to 10 workers. This in turn means that small establishments are excluded from our analysis. Vacation rentals through services such as AirBnB are not included if they are individually-owned small establishments. It is also important to note that the survey focuses on accommodation establishments. Foreign visitors who stay in the houses of their friends and/or families are not included in our analysis.

Second, the country of residence data is available only for 20 major countries as of the year 2020. The number of major countries depends upon the period. The data are available for 18 countries before April 2015 and for 16 countries before April 2013. We focus on the period between April 2015 and January 2020 such that the analysis has the same 20 countries consistently throughout the period. Third, the purpose of travel is not available by the country of residence and prefecture visited. Therefore, we cannot explore the boycott effects on tourists versus non-tourist travelers using this data. Finally, the data do not cover one-day trips since no accommodation services are involved. There are some Korean tourists who make one-day trips to Tsushima, a tiny island off Nagasaki that is closely located to Korea and has duty free shops. These cautions together imply that the survey does not cover all foreign visitors.

We exclude the period after January 2020 to exclude the effects of the travel restrictions caused by the coronavirus pandemic. As a result, the maximum number of observations is 54,520 (= 47 prefectures  $\times$  20 origin countries  $\times$  58 months).

#### 3.2 Descriptive analysis

Before going to the econometric analysis, let us first examine the basic patterns of the data. Table 1 presents the number of visitors from foreign countries, by country and by year. Table 1 indicates that Korea is one of the major origin countries of foreign visitors to Japan for the last five years. However, the number of Korean visitors dropped by 2.24 million (personnights) from 2018 to 2019, while the total number of foreign visitors increased by 17.7 million (personnights). As a result, the Korean share of total visitors declined from 14.3 percent in 2018 to 9.6 percent in 2019.

<sup>&</sup>lt;sup>19</sup>Instead, we use visitor survey data in Section 4.3 to explore possible differences in boycott effects between tourists and non-tourist visitors from Korea.

<sup>&</sup>lt;sup>20</sup>In addition to the 10 countries listed for 2019 in Table 1, the other major countries by ISO country code included in this study are: CAN, DEU, ESP, IDN, IND, ITA, MYS, PHL, RUS, and VNM.

	Ι	Table 1: Number of Visitors in Japan from Foreign Countries, by Country	nber of V	/isitors in J	apan fro	m Foreign	Countri	es, by Cour	ntry	
		2015		2016		2017		2018		2019
	Total	60,509		64,067		72,934		83,566		101,306
Rank		(100.0%)		(100.0%)		(100.0%)		(100.0%)		(100.0%)
<u></u>	CHIN	16,295	CHIN	16,867	CHIN	17,596	CHIN	22,166	CHIN	29,848
		(26.9%)		(26.3%)		(24.1%)		(26.5%)		(29.5%)
2	TWN	10,491	TWN	10,529	TWN	11,390	TWN	12,104	TWN	13,471
		(17.3%)		(16.4%)		(15.6%)		(14.5%)		(13.3%)
8	KOR	6,741	KOR	7,740	KOR	11,020	KOR	11,955	KOR	9,715
		(11.1%)		(12.1%)		(15.1%)		(14.3%)		(%9.6%)
4	HKG	4,809	HKG	5,209	HKG	6,259	HKG	6,214	USA	7,278
		(%6.2)		(8.1%)		(8.6%)		(7.4%)		(7.2%)
D	USA	3,799	USA	4,293	USA	4,782	USA	5,576	HKG	6,982
		(6.3%)		(9.7%)		(%9.9)		(6.7%)		(%6.9)
9	THA	2,396	THA	2,394	THA	2,605	THA	5,969	THA	3,604
		(4.0%)		(3.7%)		(3.6%)		(3.6%)		(3.6%)
7	AUS	1,472	AUS	1,597	AUS	1,809	AUS	2,130	AUS	3,066
		(2.4%)		(2.5%)		(2.5%)		(2.5%)		(3.0%)
8	SGP	1,379	SGP	1,516	SGP	1,702	SGP	1,961	SGP	2,455
		(2.3%)		(2.4%)		(2.3%)		(2.3%)		(2.4%)
6	GBR	906	GBR	926	GBR	1,065	GBR	1,214	GBR	2,093
		(1.5%)		(1.5%)		(1.5%)		(1.5%)		(2.1%)
10	MYS	840	MYS	934	IDN	1,001	IDN	1,184	FRA	1,564
		(1.4%)		(1.5%)		(1.4%)		(1.4%)		(1.5%)
Top 10		49,129		52,035		59,228		67,472		920'08
		(81.2%)		(81.2%)		(81.2%)		(80.7%)		(20.67)

Notes: The number of foreign visitors indicates the number of people who reside outside of Japan times the number of nights stayed in Japan (unit: 1,000 person-nights). Figures in parenthesis indicate the share (percentage). Countries are represented by ISO country codes.

Source: Japan Tourism Agency (2020) Overnight Travel Statistics Survey.

Figure C1 presents the number of visitors from Korea in 2018 and 2019, by prefecture. The prefectures are sorted by the number of visitors in 2018. This figure shows that the degree of the decline varies across prefectures. The significant decreases are concentrated in some specific prefectures such as Osaka, Fukuoka, Okinawa, Hokkaido and Oita. Table 1 confirmed that the number of foreign visitors from Korea dropped by 2.24 million from 2018 to 2019. The decline in the sum of these five regions amounted to 1.81 million. Almost 81 percent of the decline is concentrated in these five prefectures.

Figure 4 indicates the relationship between the percentage changes in the number of visitors from Korea in 2018 and 2019 and the average share of visitors from Korea between April 2015 and June 2019. The horizontal axis corresponds to the share presented in Figure 2 while the vertical axis corresponds to the percentage change between 2018 and 2019 in Figure C1. This figure shows a strong negative correlation between them (r = -0.289). This result suggests that the prefectures with high dependency on visitors from Korea are more likely to be affected by the boycott. Note, however, that this figure presents a correlation rather than a causation. Our next section investigates this relationship, based on a more rigorous econometric framework.

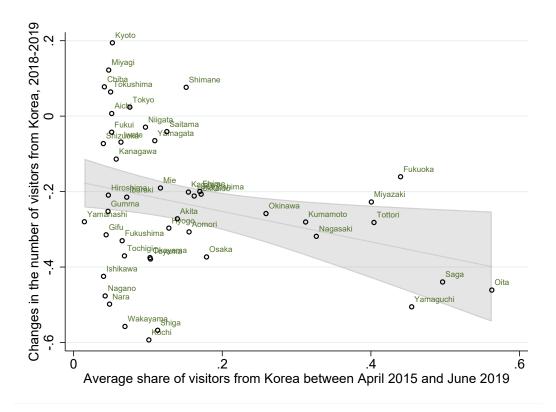


Figure 4: Changes in the Number of Visitors and the Share of Visitors from Korea

Notes: The vertical axis indicates the log difference in the number of visitors from Korea between 2018 and 2019, by prefecture. The horizontal axis indicates the share of visitors from Korea between April 2015 and June 2019. The solid line indicates the fitted values from the linear ordinary least squares estimation and the gray areas indicate the 95 percent confidence interval (CI).

Source: Japan Tourism Agency (2020) Overnight Travel Statistics Survey.

## 4 Disaggregate-level Analysis

### 4.1 Methodology

A recent study by Caselli et al. (2020) asserted the importance of country diversification of exports in reducing economic volatility.<sup>21</sup> This in turn implies that the effects of the boycott could be heterogeneous across prefectures. Specifically, the more a prefecture depends upon exports to Korea, the larger the export decline they face as a result of the boycott. We begin by analyzing the disaggregate impacts of the boycott, focusing on each prefecture's exports of accommodation services by country. Our question is: do prefectures with higher pre-boycott dependency on Korea suffer larger declines in exports to Korea as a result of the consumer boycott?

To evaluate the impact of the boycott on region-level exports, this paper employs the DDD design (Wooldridge, 2007). The DDD design allows us to estimate a model of exports from prefecture i in Japan to trading partners j at time t at monthly frequency,  $Y_{ijt}$ . We hypothesize that a prefecture's exports to Korea are more likely to be affected by the boycott if its pre-boycott export dependency on Korea is high. Note that regional dependency on visitors from Korea can be described not by a binary variable but by a continuous variable. Following Guadalupe and Wulf (2010), we treat the treatment group as a continuous variable (i.e., differing levels of exposure to treatment). Note that the number of foreign visitors is affected by other factors such as prefecture-specific tourism resources and/or country-specific factors. For example, some prefectures such as Oita attract visitors because they have nice hot springs. Similarly, the number of visitors from China and Korea is large simply because of their proximity to Japan. To control for such prefecture- and country-specific factors, we include prefecture- and country-fixed effects. Our regression equation thus is written as follows:

$$Y_{ijt} = \alpha + \psi_i + \psi_j + \psi_t$$
  
 
$$+\beta_1(s_i \times \text{Post}_t) + \beta_2(s_i \times \text{KOR}_j) + \beta_3(\text{KOR}_j \times \text{Post}_t)$$
  
 
$$+\gamma(s_i \times \text{KOR}_j \times \text{Post}_t) + \varepsilon_{ijt},$$
 (1)

where  $\psi_i$ ,  $\psi_j$ , and  $\psi_t$  are prefecture-, country-, and time-fixed effects, respectively;  $s_i$  is prefecture i's dependency on exports to Korea that is measured by the average share of visitors from Korea to total visitors from foreign countries in prefecture i before the boycott (i.e., between April 2015 and June 2019), which corresponds to the average shares shown in Figures 2 and 4; KOR $_j$  is a dummy variable taking the value one if export destination j is Korea and zero otherwise; Post $_t$  is the post-boycott dummy that takes the value one after the boycott started (i.e., from July 2019); and  $\varepsilon_{jt}$  is an error term. Note that  $s_i$  and KOR $_j$  cannot be included by themselves due to the collinearity with  $\psi_i$  and  $\psi_j$ , respectively. The parameter of interest is  $\gamma$  that captures the differential effect of the boycott on prefectures according to their dependency

<sup>&</sup>lt;sup>21</sup>Similarly, Kurz and Senses (2016) examined the effects of trade on employment volatility, using US firm-level data. They found that an increase in the number of export destinations was associated with lower levels of volatility, which is in line with the diversification story.

<sup>&</sup>lt;sup>22</sup>The DDD design is also called the triple difference design. For a recent application, see Muralidharan and Prakash (2017).

on visitors from Korea prior to the start of the boycott.<sup>23</sup> To check the robustness of our results to the strictest possible model specification, we also estimate our parameter of interest using prefecture-time ( $\psi_{it}$ ), country-time ( $\psi_{jt}$ ) and prefecture-country fixed effects ( $\psi_{ij}$ ).

For  $Y_{ijt}$ , we focus on exports of tourism services from prefecture i to country j in time t. We measure exports  $Y_{ijt}$  by the number of visitors (i.e., person-accommodation-nights) from country j to prefecture i at time t (year-month). For convenience in interpreting estimated coefficients, we use the log value of the number of foreign visitors as the dependent variable.<sup>24</sup>

In applying the DDD design to equation (1), we utilize three sets of sample data. The first sample is a full-period sample for April 2015–January 2020. The second sample is a medium-period sample for July 2018–January 2020, which covers the period one year before and six months after the boycott started (i.e., July 2019). The third sample is a short-period sample for January 2019–January 2020, which covers the period six months before and after the boycott started. The numbers of observations are 52,879, 17,573, and 12,037 for the full-, medium-, and short-period samples, respectively, due to the observations with zero trade.

Note that one of the key assumptions behind the DDD design is a common trends assumption: in the absence of treatment (i.e., the boycott in our study), the difference between the treatment and control groups is constant over time. One strategy to evaluate this assumption is to check group-specific linear trends (Wing, Simon, and Bello-Gomez, 2018). This amounts to a regression of the outcome on the treatment variable, group- and period-fixed effects, and each group effect interacted with a linear time index. In the context of our analysis, the regression equation is written as follows:

$$Y_{ijt} = \alpha + \psi_i + \psi_j + \psi_t + \eta_1(s_i \times KOR_j) + \eta_2(s_i \times Trend_t) + \eta_3(KOR_j \times Trend_t) + \lambda(s_i \times KOR_j \times Trend_t) + \varepsilon_{ijt},$$
(2)

where Trend<sub>t</sub> is a time trend; and the definitions of the variables are the same as that of equation (1). Similar to equation (1),  $s_i$ , KOR<sub>j</sub>, and Trend<sub>t</sub> cannot be included by themselves due to the collinearity with  $\psi_i$ ,  $\psi_j$ , and  $\psi_t$ .

The sample for equation (2) is before July 2019 when the boycott started. The numbers of observations for the test of the common trends assumption are 46,380, 11,074, and 5,538 for the full-, medium-, and short-period samples, respectively. If the trend is common between prefectures as well as between Korea and other countries,  $\lambda$  will be insignificant.

#### 4.2 Estimation results

Let us first check the common trends assumption. Table 2 presents the regression results for equation (2). The standard errors are clustered by prefecture, country, and time.<sup>25</sup> Columns (1), (2), and (3) present the results for the full-, medium-, and short-period samples, respectively. This table indicates that the estimated coefficients are insignificant for the full- and medium-period samples while it is significant for the short-period sample. This result supports the

<sup>&</sup>lt;sup>23</sup>We explore an explanation for this differential effect in Section 4.3.

<sup>&</sup>lt;sup>24</sup>Note that the use of the log of exports results in dropping observations with zero trade, which may lead to biases in estimated coefficients. We address this issue in Section 6.

<sup>&</sup>lt;sup>25</sup>Multi-way clustered standard errors are computed by the stata command reghdfe developed by Correia (2017).

validity of the common trends assumption for only the full- and medium-period samples, so we proceed with the DDD regression analysis using these two samples.<sup>26</sup>

Table 2: Common Trends Assumption: Disaggregate-level Analysis

(1)	(2)	(3)
2015m4	2018m7	2019m1
-2019m6	-2019m6	-2019m6
0.009	0.030	-0.431***
[0.006]	[0.031]	[0.008]
Yes	Yes	Yes
Yes	Yes	Yes
Yes	Yes	Yes
Yes	Yes	Yes
Yes	Yes	Yes
Yes	Yes	Yes
46,380	11,074	5,538
0.85	0.86	0.87
	2015m4 -2019m6 0.009 [0.006] Yes Yes Yes Yes Yes Yes Yes 46,380	2015m4 2018m7 -2019m6 -2019m6  0.009 0.030 [0.006] [0.031]  Yes

Notes: Figures in brackets indicate standard errors clustered by country, prefecture, and time. \*\*\* indicates the significance level at 1 percent.

Source: Authors' estimation, based on Overnight Travel Statistics Survey.

Table 3 presents the DDD regression results. Columns (1) and (2) are the estimation results for equation (1) for the full- and medium-period samples, respectively. There are two notable findings. First, the coefficients of  $(KOR_j \times Post_t)$  indicate significantly negative signs. The coefficients are -0.553 and -0.529 for the full- and medium-period samples, respectively. This result indicates that the effect of the consumer boycott on exports to Korea is between -41.1 percent and -42.5 percent, after converting the coefficients of log changes into growth rates due to the large estimated impacts.<sup>27</sup> Even after we control for the prefecture-, country-, and time-fixed effects, the negative effects of the boycott on exports to Korea are remarkably large at their minimum value (i.e., for a hypothetical prefecture with zero Korea dependency pre-boycott). Second, the coefficient of  $(s_i \times KOR_j \times Post_t)$ , our parameter of interest, presents significantly negative signs. This result suggests that the effects of the boycott on exports to Korea are different across prefectures in Japan based on their pre-boycott Korea dependency. The estimation results in columns (3) and (4) of Table 3 demonstrate that our parameter of interest results do not change much even when we use the strictest possible DDD model specification (i.e., with prefecture-time, country-time and prefecture-country fixed effects).<sup>28</sup>

One may be interested in the economic significance as well as the statistical significance. While our study is not based on a general equilibrium framework, we can compute the eco-

<sup>&</sup>lt;sup>26</sup>It is more difficult to satisfy the common trends assumption using only six months in the short-period sample in the presence of differences in travel seasonality across countries of origin.

<sup>&</sup>lt;sup>27</sup>Coefficients are converted into approximate growth rates as follows: growth rate =  $\exp(\operatorname{coefficient}) - 1$ .

<sup>&</sup>lt;sup>28</sup>The prefecture-time fixed effect controls for prefecture-time specific factors such as the utilization rate of accommodation services at the prefecture level. Similarly, the country-time fixed effect controls for country-time specific factors such as country-specific seasonality and exchange rate movement. The country-prefecture fixed effect controls for country-prefecture-specific factors such as the existence of international schools and towns (e.g., China town).

Table 3: Regression Results: Disaggregate-level Analysis

O		00 0		,
	(1)	(2)	(3)	(4)
Period	2015m4	2018m7	2015m4	2018m7
	-2020m1	-2020m1	-2020m1	-2020m1
$s_i \times \mathrm{Post}_t$	0.238*	0.346***		
	[0.131]	[0.108]		
$s_i \times KOR_j$	8.156***	8.263***		
·	[0.340]	[0.441]		
$KOR_i \times Post_t$	-0.553***	-0.529***		
·	[0.032]	[0.028]		
$s_i \times \text{KOR}_i \times \text{Post}_t$	-2.270***	-2.373***	-2.286***	-2.380***
·	[0.146]	[0.093]	[0.157]	[0.148]
Fixed effect				
Prefecture $(\psi_i)$	Yes	Yes	No	No
Country $(\psi_j)$	Yes	Yes	No	No
Time $(\psi_t)$	Yes	Yes	No	No
Prefecture-time ( $\psi_{it}$ )	No	No	Yes	Yes
Country-time ( $\psi_{jt}$ )	No	No	Yes	Yes
Prefecture-country $(\psi_{ij})$	No	No	Yes	Yes
$\overline{N}$	52,879	17,573	52,879	17,573
$R^2$	0.85	0.85	0.95	0.96

Notes: Figures in brackets indicate standard errors clustered by country, prefecture, and time. \*\*\* and \* indicate the significance level at 1 and 10 percent, respectively.

Source: Authors' estimation, based on Overnight Travel Statistics Survey.

nomic magnitude based on the estimated coefficients from our main specification and prefecture i's dependency on exports to Korea,  $s_i$ , as a back-of-the-envelope calculation. Table 4 presents the distribution of  $s_i$  and the estimated economic magnitude of the boycott's effects. The average and the median of  $s_i$  are 14.9 percent and 10.3 percent, respectively, while the first and third quartiles are 5.1 percent and 17.0 percent, respectively. The results indicate the heterogenous impacts of the boycott. For example in the case of the full-period sample, the impact is approximately -11.6 percent (=  $-2.270 \times 5.1$ ) for the 25th percentile prefecture while it is roughly -38.5 percent (=  $-2.270 \times 17.0$ ) for the 75th percentile prefecture. Due to the large estimated changes in log values, these relative magnitude effects can be considered rough estimates of the growth rates of -11.0 percent and -32.0 percent, respectively.

Note that these results are based on the comparison of exports to Korea between prefectures. In order to calculate the effect on exports relative to other countries, we need to tally the total magnitude using the coefficients of  $(KOR_j \times Post_t)$  and  $(s_i \times KOR_j \times Post_t)$ , as shown in columns (4) and (5) of Table 4.<sup>30</sup> Using the longer two sample periods, which satisfied the common trends assumption, a 25th percentile prefecture suffers a 47.8 to 48.8 percent loss in exports to Korea while a prefecture at the 75th percentile suffers a loss of 60.6 to 60.9 percent.<sup>31</sup>

<sup>&</sup>lt;sup>29</sup>A similar exercise has been done in recent studies on the effects of offshoring. See, for example, Harrison and McMillan (2011) and Kambayashi and Kiyota (2015).

<sup>&</sup>lt;sup>30</sup>The values in column (4) can be interpreted as percentage point differences in average growth rates between the treated and control groups, while the values in column (5) are approximate average treatment effects on the treated in growth rate terms.

<sup>&</sup>lt;sup>31</sup>Our estimated effects of the boycott on Japan's exports of accommodation services to Korea are admittedly

The implied gap between the 75th and 25th percentile prefectures is -12.1 to -12.8 percentage points, depending on the sample period. Using the full-period sample, for prefectures with high dependency on Korean visitors, the negative impact on their exports of accommodation services to Korea is 12.1 percentage points larger than that for prefectures with low dependency. The results clearly indicate that prefectures with higher dependency on visitors from Korea are more likely to have severe declines in exports of accommodation services to Korea. We explore the explanation for this disproportionate boycott effect in Section 4.3 using an alternate dataset that allows us to estimate tourists versus non-tourist travelers from Korea.

Table 4: Impact of the Boycott on Prefectures' Exports to Korea

	(1)	(2)	(3)	(4)	(5)
			$(=(1)\times(2))$	(=(3) + KP Coeff.)	Total magnitude
Percentile	Coefficient	$s_i$	Relative magnitude	Total magnitude	converted
			(log change)	(log change)	(growth rate)
2015m4-202	0m1				
Mean	-2.270	0.149	-0.339	-0.892	-0.590
25%	-2.270	0.051	-0.116	-0.669	-0.488
50%	-2.270	0.103	-0.233	-0.786	-0.544
75%	-2.270	0.170	-0.385	-0.938	-0.609
75-25% gap					-0.121
2018m7-202	0m1				
Mean	-2.373	0.149	-0.355	-0.884	-0.587
25%	-2.373	0.051	-0.121	-0.650	-0.478
50%	-2.373	0.103	-0.244	-0.773	-0.538
75%	-2.373	0.170	-0.403	-0.932	-0.606
75-25% gap					-0.128

Notes: Exports to Korea mean the exports of accommodation services to Korea that are defined as the number of visitors from Korea (the total number of visitors who reside in Korea  $\times$  the number of nights stayed in Japan). Percentile indicates the quartiles of  $s_i$ . Coefficients are obtained from Table 3 and KP Coeff. means (KOR $_j \times \text{Post}_t$ ) coefficient from the corresponding sample period. Rounding off of displayed numbers explains small variations in calculated numbers shown above. Growth rate = exp(log change) -1.

Source: Authors' estimation, based on Overnight Travel Statistics Survey.

It is also important to note that stopping travel to Japan affects Korea as well as Japan because many Korean tourists utilize Korean airlines and travel agencies. In this context, we should note that some studies such as Du, Ju, Ramirez, and Yao (2019) and Clerides et al. (2015) argue that the impact of political conflict is short-lived. Although this is a related important question, we are not able to analyze this issue because travel between countries is restricted from February 2020 in many countries due to the coronavirus pandemic.<sup>32</sup>

quite large, but the magnitudes are actually smaller than those reported for bilateral beer trade. Korean imports of Japanese beer basically stopped from August, 2019 (i.e., approximately -100 percent monthly change), leading to a -49.2 percent annual change for 2019 (Stangarone, 2020).

<sup>&</sup>lt;sup>32</sup>Instead, we refer the reader back to footnote 17 where we mentioned suggestive evidence that an easing of bilateral tensions in November, 2019, may be linked to a small upturn in visitors from Korea to Japan from that month through January, 2020.

#### 4.3 Tourists versus non-tourist visitors

We now turn to the task of explaining why some prefectures in Japan are disproportionately impacted by the Korean consumer boycott at the bilateral (i.e., disaggregate) level. As stated previously in Section 3, our main data (i.e., visitor-night accommodations) does not provide the purpose of travel by the country of residence and prefecture visited. This data limitation leads us to implicitly assume that travelers from Korea are a homogeneous group with a common propensity to participate in the consumer boycott of travel to Japan. However, our disaggregate-level results (i.e., finding that prefectures that are more dependent on visitors from Korea suffer larger *percentage* losses in visitors from Korea) are inconsistent with this assumption.

Suppose that 50 percent of Koreans travelers chose to participate in the consumer boycott of travel to Japan.<sup>33</sup> In that case, we would expect that prefectures with higher dependency on visitors from Korea would suffer larger percentage losses in their exports of accommodations services at the aggregate level (i.e., a 50 percent decline in visitors from Korea is more impactful for a prefecture with a 40 percent dependence on such visitors than for one with only a 10 percent dependence), which we address in the next section. At the disaggregate level, we would expect to see each prefecture lose 50 percent of its Korean visitors, which would be indicated by a negative and significant coefficient for  $(KOR_j \times Post_t)$  but not for  $(s_i \times KOR_j \times Post_t)$ . Instead, our disaggregate-level results indicate a *disproportionate* boycott effect based on a prefecture's pre-boycott Korea dependency (i.e., a significant coefficient on the  $(s_i \times KOR_j \times Post_t)$  coefficient).

To explain the disproportionate boycott effect at the disaggregate level, we need to acknowledge that visitors from Korea are not homogenous but rather heterogeneous in terms of their propensities to participate in the boycott and heterogenous in where they travel within Japan. Leisure travelers (i.e., tourists) may be more likely to participate in a consumer boycott since leisure travel is more discretionary in terms of destination and timing than other types of travel (e.g., travel for business, to visit family or friends, to attend school, etc.). Leisure travelers also favor some destinations in Japan over others. If the same prefectures that have high pre-boycott dependency on visitors from Korea also tend to attract Korean tourists, rather than non-tourist Korean travelers, then that can explain our finding of disproportionate bilateral boycott effects based on Korea dependency.

To examine this hypothesis, we use information on visitors' purpose of travel collected by the Japan Tourism Agency's *Consumption Trend Survey for Foreigners Visiting Japan (Hounichi Gaikokujin Shouhi Doukou Chousa* in Japanese). This survey provides data on a quarterly basis for visitors to Japan who are surveyed at their port of entry or departure. We use this data to create a "Korean tourist dependency" measure to see to what extent each prefecture depends on Korean tourists relative to all Korean visitors in the pre-boycott period, and then we compare this measure to our previously defined "Korea dependency" based on the visitor-night

<sup>&</sup>lt;sup>33</sup>Note that this may be a conservative estimate. One online survey of Koreans collected in late August to early September, 2019, found that 69.3 percent of respondents who had planned to visit Japan cancelled their trip or changed their destination away from Japan as a result of Japan's restriction on exports from July, 2019. (Korea Culture and Tourism Institute, 2019, available online (in Korean): survey link)

accommodations data.34

Table 5 shows this comparison by prefecture. The 47 prefectures are ranked in descending order by their level of Korea dependency (i.e., share of visitor-night accommodations for visitors from Korea out of all foreign visitor-night accommodations) shown in Column (1). Columns (2)–(4) reflect the survey data from the Consumption Trend Survey for Foreigners Visiting Japan. The correlation between Korea dependency and Korean tourist dependency is 0.5481, indicating that prefectures with high dependency on foreign visitors from Korea also tend to have high dependency on Korean tourists as opposed to Korean non-tourist travelers. For the top 10 prefectures ranked by Korea dependency (i.e., Oita to Osaka in Table 5), 80.0 to 96.4 percent of their Korean visitors are tourists. For the bottom 10 prefectures (i.e., Nara to Yamanashi), the range of Korean tourist dependency is much wider and lower at 29.0 to 77.7 percent, with the exception of Nara at 92.5 percent. If tourists are more likely than nontourists to participate in the consumer boycott, then the strong positive correlation between prefectures' Korea dependency and Korean tourist dependency helps to explain our finding of disproportionate impacts of the consumer boycott at the disaggregate level.<sup>35</sup> Our results imply that prefectures that attract more diverse visitors by purpose of travel (i.e., tourism versus non-tourism) will be less affected by a consumer boycott at the bilateral level.

## 5 Aggregate-level Analysis

### 5.1 Methodology

The previous section found that prefectures with higher dependency on visitors from Korea were more likely to have severe declines in their exports to Korea. Note, however, that the estimation results from prefecture-country-level specifications tells us the boycott effect in a "relative" sense: relative to travelers from all other foreign countries. Thus it is not necessarily clear whether a given prefecture had a "net" adverse effect from the boycott since it is possible that travelers from other countries picked up the slack induced by a reduction in travel from Korea. An aggregate prefecture-level analysis can address the prefecture-level net effect from the boycott. More specifically, this section asks the following question: do prefectures with higher pre-boycott dependency on Korea suffer larger declines in total exports as a result of the consumer boycott? Noting that our main outcome variable is exports from prefecture i in Japan to trading partners j at time t at monthly frequency,  $Y_{ijt}$ , we can compute each prefecture's total exports of accommodation services:  $Y_{it} = \sum_{j} Y_{ijt}$ .

<sup>&</sup>lt;sup>34</sup>We use the regional survey data which provides the purpose of travel by *nationality* and by prefecture visited. The national survey reports some data by nationality and by country of residence and indicates for 2018 that almost all surveyed visitors to Japan who reside in Korea are Korean nationals (i.e., 99.7 percent). This high correspondence between country of residence and nationality for visitors from Korea allows us directly to compare the visitor-night data (based on country of residence) and visitor survey data (based on nationality).

<sup>&</sup>lt;sup>35</sup>Note that the "Consumption Trend Survey for Foreigners Visiting Japan" is not used in our main DDD and DID analyses since it is only reported on a quarterly basis and we have no information as to how representative the survey is of all foreign visitors to Japan.

<sup>&</sup>lt;sup>36</sup>A similar approach is employed in the recent banking and finance literature on bank's loan supply and demand where there are many firms that borrow from multiple banks (e.g., Jiménez, Mian, Peydró, and Saurina, 2020). In our context, firm, bank, and loan can be interpreted as prefecture, country, and travelers (i.e., exports), respectively.

Table 5: Korea dependency and Korean tourist dependency

Table 5: Ko	rea depende	•		st dependency
	(1)	(2)	(3)	(4)
Prefecture	Korea	All Korean	Korean	Korean tourist
	dependency	visitors	tourists	dependency
		surveyed	surveyed	(=(3)/(2))
Total		84,658	67,629	0.7988
Oita	0.5627	9,694	9,346	0.9641
Saga	0.4965	1,218	1,020	0.8374
Yamaguchi	0.4548	1,646	1,316	0.7995
Fukuoka	0.4399	22,520	20,118	0.8933
Tottori	0.4042	292	255	0.8733
Miyazaki	0.4006	266	215	0.8083
Nagasaki	0.3266	3,212	2,867	0.8926
Kumamoto	0.3122	2,439	2,148	0.8807
Okinawa	0.2588	4,152	3,999	0.9632
Osaka	0.1788	27,002	24,078	0.8917
Kagoshima	0.1716	614	492	0.8013
Ehime	0.1698	134	76	0.5672
Hokkaido	0.1622	5,377	5,027	0.9349
	0.1553	116	86	0.7414
Aomori			534	
Kagawa Shimane	0.1545 0.1515	586 182	163	0.9113
		182		0.8956
Akita	0.1396	72	35	0.4861
Hyogo	0.1281	4,802	4,212	0.8771
Saitama	0.1254	557	224	0.4022
Mie	0.1168	233	81	0.3476
Shiga	0.1130	186	64	0.3441
Yamagata	0.1092	110	58	0.5273
Toyama	0.1034	490	399	0.8143
Okayama	0.1028	270	182	0.6741
Kochi	0.1012	59	36	0.6102
Niigata	0.0967	201	70	0.3483
Tokyo	0.0756	20,554	10 <i>,</i> 779	0.5244
Ibaraki	0.0715	241	59	0.2448
Wakayama	0.0691	186	144	0.7742
Tochigi	0.0684	276	89	0.3225
Fukushima	0.0653	88	18	0.2045
Iwate	0.0637	33	17	0.5152
Kanagawa	0.0573	2,659	1,179	0.4434
Kyoto	0.0522	13,804	12,890	0.9338
Aichi	0.0512	2,833	1,459	0.5150
Fukui	0.0512	47	11	0.2340
Tokushima	0.0497	57	39	0.6842
Nara	0.0483	2,977	2,755	0.9254
Miyagi	0.0472	336	156	0.4643
Hiroshima	0.0467	752	381	0.5066
Gumma	0.0463	169	49	0.2899
Gifu	0.0437	631	490	0.7765
Nagano	0.0424	458	238	0.5197
Chiba	0.0414	12,293	8,407	0.6839
Ishikawa	0.0403	360	212	0.5889
Shizuoka	0.0400	808	385	0.4765
Yamanashi	0.0145	280	144	0.5143
Correlation	0.0110	200	177	0.5481
Correlation				0.0401

Notes: Korea dependency in column (1) defined as the share of foreign visitors from Korea between April 2015 and June 2019 using visitor-night accommodations data. Columns (2)–(4) use survey data collected from foreign visitors to Japan at ports of entry or departure for 2015Q2 to 2019Q2. Korean tourist dependency defined as number of surveyed Korean tourists divided by total number of surveyed Korean visitors to Japan.

Source: Authors' estimation, based on *Overnight Travel Statistics Survey* (column (1)) and *Consumption Trend Survey* for Foreigners Visiting Japan (columns (2)–(4)).

The regression equation is based on a standard DID design as follows:

$$Y_{it} = \alpha + \psi_i + \psi_t + \lambda(s_i \times \text{Post}_t) + \varepsilon_{it}, \tag{3}$$

where the definitions of variables are the same as those in the previous section. The  $s_i$  term captures a type of "exposure to treatment", with the consumer boycott as the "treatment" in this standard DID design. The parameter of interest is  $\lambda$  that captures the differential effect of pre-boycott dependency on Korea across prefectures. The numbers of observations are 2,726 (= 47 prefectures  $\times$  58 months), 893 (= 47 prefectures  $\times$  19 months), and 611 (= 47 prefectures  $\times$  13 months) for the full-, medium-, and short-period samples, respectively. Note that  $s_i$  cannot be included by itself because of the collinearity with  $\psi_i$ .

The corresponding regression to evaluate the common trends assumption is as follows:

$$Y_{it} = \alpha + \psi_i + \psi_t + \zeta(s_i \times \text{Trend}_t) + \varepsilon_{it}, \tag{4}$$

where Trend<sub>t</sub> is a time trend; and the other variables are the same as above. The sample for equation (4) is before July 2019 when the boycott started. The numbers of observations for the test of the common trends assumption thus are 2,397 (= 47 prefectures  $\times$  51 months), 564 (= 47 prefectures  $\times$  12 months), and 282 (= 47 prefectures  $\times$  6 months) for the full-, medium-, and short-period samples, respectively. If the trend is common between prefecture,  $\zeta$  will be insignificant.

#### 5.2 Estimation results

We first check the common trends assumption. Table 6 presents the regression results for equation (4). Columns (1), (2), and (3) present the estimation results for the full-, medium-, and short-period samples, respectively. The coefficient is insignificant for the full- and medium-period samples, but it is significant at the 10 percent level for the short-period sample. This result supports the validity of the common trends assumption for the longer two samples.

Table 6: Common Trends Assumption: Aggregate-level Analysis

	(1)	(2)	(3)
Period	2015m4	2018m7	2019m1
	-2019m6	-2019m6	-2019m6
$s_i \times \mathrm{Trend}_t$	0.003	-0.032	-0.157*
	[0.007]	[0.024]	[0.075]
Fixed effect			
Prefecture $(\psi_i)$	Yes	Yes	Yes
Time $(\psi_t)$	Yes	Yes	Yes
$\overline{N}$	2,397	564	282
$R^2$	0.97	0.98	0.98

Notes: Figures in brackets indicate standard errors clustered by prefecture and time. \* indicates the significance level at 10 percent.

Source: Authors' estimation, based on Overnight Travel Statistics Survey.

Table 7 presents the DID regression results. Columns (1) and (2) show the results for the

full- and medium-period samples, respectively. Table 7 indicates significantly negative coefficients of  $(s_i \times \text{Post}_t)$  for both types of sample. This confirms that prefectures with higher dependency on visitors from Korea are more likely to face significantly negative impacts due to the boycott. In the disaggregate-level analysis in Section 4, we confirmed the negative effects of the boycott on the exports of accommodation services to Korea. The results of Table 7 suggest that this negative impact is too large to be offset by any potential increases in exports to other countries. As a result, Japanese prefectures had net adverse effects from the boycott and these adverse effects increased in prefectural dependency on Korean exports.

Table 7: Regression Results: Aggregate-level Analysis

	(1)	(2)
Period	2015m4	2018m7
	-2020m1	-2019m6
$s_i \times \mathrm{Post}_t$	-0.841***	-0.775***
	[0.183]	[0.152]
Fixed effect		
Prefecture $(\psi_i)$	Yes	Yes
Time $(\psi_t)$	Yes	Yes
$\overline{N}$	2,726	893
$R^2$	0.97	0.98

Notes: Figures in brackets indicate standard errors clustered by prefecture and time. \*\*\* indicates the significance level at 1 percent.

Source: Authors' estimation, based on Overnight Travel Statistics Survey.

Table 8: Impact of the Boycott on Prefectures' Total Exports

	1	J		1
	(1)	(2)	(3)	(4)
			$(=(1) \times (2))$	Total magnitude
Percentile	Coefficient	$s_i$	Total magnitude	converted
			(log change)	(growth rate)
2015m4-2020	0m1			
Mean	-0.841	0.149	-0.126	-0.118
25%	-0.841	0.051	-0.043	-0.042
50%	-0.841	0.103	-0.086	-0.083
75%	-0.841	0.170	-0.143	-0.133
75-25% gap				-0.091
2018m7-2020	0m1			
Mean	-0.775	0.149	-0.116	-0.109
25%	-0.775	0.051	-0.040	-0.039
50%	-0.775	0.103	-0.080	-0.077
75%	-0.775	0.170	-0.132	-0.123
75-25% gap				-0.084

Notes: Exports mean the exports of accommodation services that are defined as the number of foreign visitors (the total number of visitors who reside outside of Japan  $\times$  the number of nights stayed in Japan). Percentile indicates the quartiles of  $s_i$ . Coefficients are obtained from Table 7. Rounding off of displayed numbers explains small variations in calculated numbers shown above. Growth rate =  $\exp(\log \operatorname{change}) - 1$ .

Source: Authors' estimation, based on Overnight Travel Statistics Survey.

Table 8 computes the magnitude of these effects in log changes (i.e., percentage point differ-

ences in average growth rates between the treated and control groups) and then converted to growth rates (i.e., approximate average treatment effects on the treated in growth rate terms) across the distribution of  $s_i$  as before. Table 8 indicates that the total exports of each prefecture declined, on average, between 11.8 percent and 10.9 percent for the full- and medium-period samples, respectively. The results suggest that the impacts on each prefecture's total exports are around -11.3 percent on average. Although these export effects are significantly larger than those of the previous studies such as Heilmann (2016), a caution may be needed because total exports in our study mean total exports of accommodation services only, not exports of all goods and services.<sup>37</sup>

Another notable finding is that the impacts vary across prefectures. Some regions had large negative aggregate impacts on their accommodations industry from the boycott. Table 8 shows not only the mean of  $s_i$  but also the 1st, 2nd, and 3rd quartiles of  $s_i$  as 5.1, 10.3 and 17.0 percent, respectively. As shown in Table 8, these values of  $s_i$  imply impacts of -4.2, -8.3 and -13.3 percent for the 25th, 50th and 75th percentile prefectures, respectively, for the full-period sample. The gap between the 75th and 25th percentile prefectures is quite large at -9.1 percentage points which exceeds the estimated loss for the 50th percentile prefecture (i.e., -8.3 percent). The results suggest the importance of considering regional heterogeneity within Japan in assessing the impacts of the consumer boycott.

Our results also have an important policy implication. While the negative impact of political conflict on trade could be small for a country as a whole, it could have significant effects on trade for particular regions. Such regional heterogeneity might result in the expansion of inequality between regions. It thus is important for policy makers to take into account such regional impacts as a consequence of political conflict.

#### 6 Discussion

#### 6.1 Timing

For the decline in exports to be attributable to the boycott, prefecture i's dependency on exports to Korea,  $s_i$ , should be correlated with exports after the boycott, but not before. To determine whether there is a relationship between a prefecture's Korea dependency and exports in the period before July 2019, we replace the post-boycott dummy Post $_t$  with a full set of month-year dummies, denoted as  $d_t$ . For the disaggregate-level analysis, regression equation (1) is

<sup>&</sup>lt;sup>37</sup>As mentioned above, Heilmann (2016) found that the reduction in total exports of the boycotted country was low. He argued that "even though an individual firm of the boycotted country might be hit hard, the overall effect on the export sector is small" (Heilmann, 2016, p.180). This argument is consistent with our finding. Also note one additional difference between our study and previous ones is that our estimates are for trade volume while other studies have tended to use trade values.

<sup>&</sup>lt;sup>38</sup>A similar approach is introduced in Pierce and Schott (2016).

rewritten as follows:

$$Y_{ijt} = \alpha + \psi_i + \psi_j + \psi_t$$

$$+ \sum_t \beta_{1t}(s_i \times d_t) + \beta_2(s_i \times KOR_j) + \sum_t \beta_{3t}(KOR_j \times d_t)$$

$$+ \sum_t \gamma_t(s_i \times KOR_j \times d_t) + \varepsilon_{ijt}.$$
(5)

Similarly, for the aggregate-level analysis, regression equation (3) is rewritten as follows:

$$Y_{it} = \alpha + \psi_i + \psi_t + \sum_t \lambda_t (s_i \times d_t) + \varepsilon_{it}.$$
 (6)

Figure 5 displays the 95 percent CI for the coefficients  $\gamma_t$  (light gray) and  $\lambda_t$  (dark gray) in equations (5) and (6), respectively. Standard errors are clustered by country, prefecture, and time in equation (5) and by prefecture and time in equation (6). We set July 2017 as the base level for the coefficients.<sup>39</sup> This figure indicates that the CI for both disaggregate- and aggregate-level results fluctuates between zero and one before July 2019. However, it shows a sharp drop below zero from July 2019 when the boycott started. This pattern is consistent with the timing of the boycott, lending further support for the baseline empirical strategy.

This figure also indicates a sharp drop around April 2016. As we argued in footnote 11, this is possibly attributable to the 2016 Kumamoto earthquakes on April 14th and 16th that caused severe damage in Kumamoto and Oita prefectures. The results suggest that the impact of the consumer boycott on Japan's accommodation services exports is comparable to that of the 2016 Kumamoto earthquake at the aggregate level and is much larger at the disaggregate level. This confirms the strong impact of the consumer boycott.

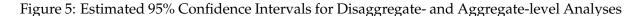
#### 6.2 Alternative estimation model

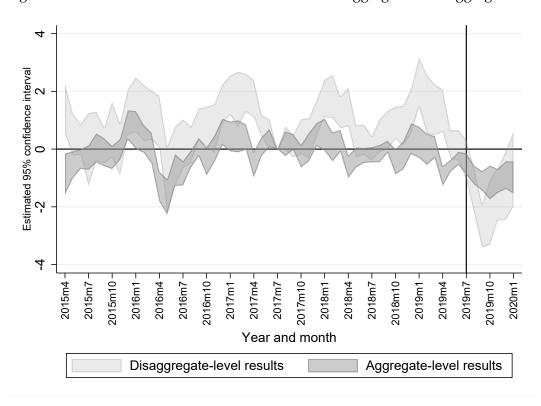
One may be concerned with the use of a log-linearized specification. Several studies have pointed out the problems of log-linearization in estimating bilateral trade flows. First, the use of log values for the dependent variable will result in discarding observations of zero trade because we cannot take the log of zero (Santos Silva and Tenreyro, 2006). Second, the log-linearized model faces severe bias when heteroskedasticity exists. Third, the sum of the fitted values in the log-linearized model does not necessarily equal the sum of the levels (Fally, 2015). Lastly, the log-linear specification described in Sections 4 and 5 implies an additive treatment effect while the true treatment effect may be multiplicative (Ciani and Fisher, 2019).

We can avoid the problems with log linearization and incorporate a multiplicative treatment effect by employing the Poisson Pseudo Maximum Likelihood (PPML) estimator (Santos Silva and Tenreyro, 2006). Full details on and results from our use of the PPML estimator appear in Appendix A, where we demonstrate that the main messages of the log-linearized

<sup>&</sup>lt;sup>39</sup>We choose July 2017 because it is around the midpoint of our sample period and is the same month (i.e., July) as when the boycott started.

<sup>&</sup>lt;sup>40</sup>In addition, the converted growth rate from the log-linear specification (i.e., column (5) in Table 4 and column (4) in Table 8) is only approximate, while that from the multiplicative model (i.e., column (5) in Table A2 and column (4) in Table A3) is in exact terms.





Notes: This figure displays the 95 percent confidence interval (CI) for the estimated difference-in-difference-in-differences (DDD) and difference-in-differences (DID) coefficients for interactions of month-year dummies with prefecture i's dependency on exports to Korea. The light-shaded CI represents the disaggregate-level (i.e., DDD) results while the dark-shaded CI represents the aggregate-level (i.e., DID) results. The baseline level is set in July 2017.

Source: Authors' estimation, based on Overnight Travel Statistics Survey.

model hold even when we employ an alternative estimation model, which indicates the robustness of our results.<sup>41</sup>

Alternatively, we can remain neutral regarding which estimation model, log-linear or PPML, is preferred to capture the boycott effects by using the estimated growth rates from both models to establish ranges for the boycott effects. In Table 9 we use both estimation models and two sample periods to establish ranges for the boycott effects, which we then use as our main results. These combined results indicate that prefectures with high dependency on visitors from Korea suffered losses in exports to Korea of 56.9 to 60.9 percent while prefectures with low Korea dependency suffered corresponding losses of 47.8 to 49.7 percent due to the consumer boycott. The gap in disaggregate effects of the boycott between the 75th percentile prefecture and the 25th percentile prefecture is -9.1 to -11.1 percentage points, or about -10 percentage points. At the aggregate level, high Korea dependency prefectures experienced reductions in their total exports of accommodation services of 10.5 to 13.3 percent while low Korea dependency prefectures faced corresponding losses of 3.3 to 4.2 percent. The gap in aggregate boycott effects between the 75th percentile prefecture and the 25th percentile prefecture for Korea dependency is -7.2 to -9.1 percentage points, which exceeds or approximates the estimated loss for the 50th percentile prefecture (i.e., -6.5 to -8.3 percent). These results illustrate the importance of considering regional heterogeneity in examining boycott effects.

In addition, our main results imply that "angry consumers" can have significant economic effects that extend beyond bilateral trade alone. As shown in Table 9, the average prefecture suffered bilateral (i.e., Japan to Korea) export losses of 55.7 to 59.0 percent and aggregate export losses of 9.3 to 11.8 percent. These aggregate effects are relevant for estimating the net losses to the accommodations and related traveler services industries in Japan, along with the accompanying losses in services tax revenues. However, the much larger bilateral effects are most relevant for considering the unintended victims of the consumer boycott, which are Korean airlines and travel agencies offering Korea-Japan routes and travel packages.

#### 6.3 Overall exports and demand shock in Korea

Since we focus on a single political conflict, we can also aggregate exports along an alternative dimension:  $Y_{jt} = \sum_i Y_{ijt}$ , where prefecture exports of accommodation services are aggregated to the national level. Then we can ask whether the overall accommodation services exports of Japan to Korea relative to other countries declined as a result of the boycott. Because the boycott occurs only in Korea during this period, the exports to other countries should not be affected. Thus, we can hypothesize that a decline in exports after the boycott is observed only for exports to Korea. To answer this question, similar to Subsection 6.1, we run the following regression:

$$Y_{jt} = \alpha + \psi_j + \psi_t + \sum_t \rho_t(KOR_j \times d_t) + \varepsilon_{jt}, \tag{7}$$

<sup>&</sup>lt;sup>41</sup>We also demonstrate the robustness of our results to the use of an alternative diversification measure (Appendix B) and to the exclusion of outliers (Appendix C).

<sup>&</sup>lt;sup>42</sup>We estimate the boycott's revenue effects in Section 6.4.

<sup>&</sup>lt;sup>43</sup>Kim (2019) quotes Gwang-ok Kim, general manager of the Korea Aviation Association, as stating that the number of travelers on Korea-Japan routes declined by 43 percent in October, 2019, compared to the same month in 2018. We leave a more thorough examination of the "backfire effect" of the boycott for future research.

Table 9: Summary of Estimated Boycott Effects Across Two Estimation Models and Two Sample Periods

	Disggregate-level analysis		Aggregate-level analysis		
	(1)	(2)	(3)	(4)	
Percentile	Max	Min	Max	Min	
Mean	-0.557	-0.590	-0.093	-0.118	
25%	-0.478	-0.497	-0.033	-0.042	
50%	-0.528	-0.544	-0.065	-0.083	
75%	-0.569	-0.609	-0.105	-0.133	
75-25% gap	-0.091	-0.111	-0.072	-0.091	

Notes: Max and min values from growth rates estimated using log linear estimation (shown in Tables 4 and 8) and PPML estimation (shown in Tables A2 and A3) across both sample periods that met the common trends assumption (i.e., the full- and medium-period samples).

Source: Authors' estimation, based on Overnight Travel Statistics Survey.

where the variables are the same as before. We measure  $Y_{jt}$  as the log of the number of visitors from foreign country j to Japan at time t (year-month). The parameter of interest is  $\rho_t$  that captures the differential effect of visitors from Korea relative to visitors from other countries.

First we test the common trends assumption using the aggregated export data. We find that the common trends assumption is not met for this analysis. <sup>44</sup> Thus it is difficult to identify the causal impact of the boycott on Japan's aggregate bilateral exports of accommodation services. Therefore, we present the results from equation (7) just as a reference, not as a main result. Figure 6 plots the estimated 95 percent CI of  $\rho_t$  for the full sample, similar to the aggregate-level results in Figure 5. We set July 2017 as the base level for the coefficients as in Figure 5. We can confirm that the CI declined sharply from July 2019. Although it may not be attributable to the consumer boycott, we can at least state that visitors to Japan from Korea relative to other origin countries dropped significantly from July 2019.

In this connection, one may be concerned that the sharp drop in visitors from Korea to Japan may come from an overall demand shock in Korea, rather than from the consumer boy-cott targeting Japan, as was pointed out in Section 1. Under this alternative hypothesis, an overall demand shock in Korea causes Korean residents to sharply curtail their travel abroad. If this is the case, we expect that Korean outbound travel dropped not only to Japan but also to other destinations. This in turn means that the travel from Korea to Japan relative to other destination countries will not show significant differences after the boycott. In order to investigate this possibility, we run the following regression, using data from Korea:<sup>45</sup>

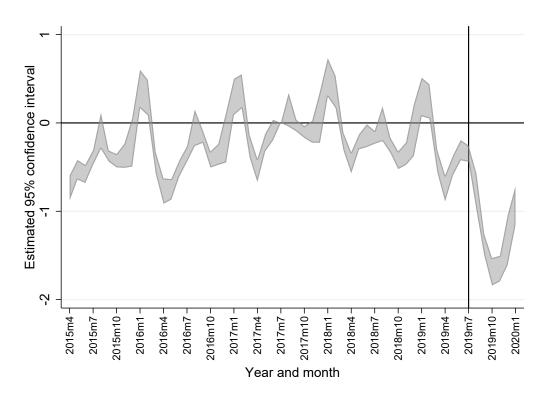
$$Y_{jt} = \alpha + \psi_j + \psi_t + \sum_t \chi_t(\text{JPN}_j \times d_t) + \varepsilon_{jt},$$
 (8)

where  $Y_{jt}$  is now (the log of) the number of departures from Korea to country j; JPN $_j$  is the Japan dummy that takes the value one if the destination country is Japan and zero otherwise;  $d_t$  is time (i.e., year-month) dummy. We focus on the period between April 2015 and January 2020. If the negative demand shock from July 2019 is specific to Japan, we expect significantly

<sup>&</sup>lt;sup>44</sup>Detailed results on the test of the common trends assumption are presented in Appendix D.

<sup>&</sup>lt;sup>45</sup>The Korean data are obtained from the Korea Tourism Organization website. The unit is number of departures.

Figure 6: Number of Visitors from Korea to Japan Relative to Other Origin Countries: Japanese Data



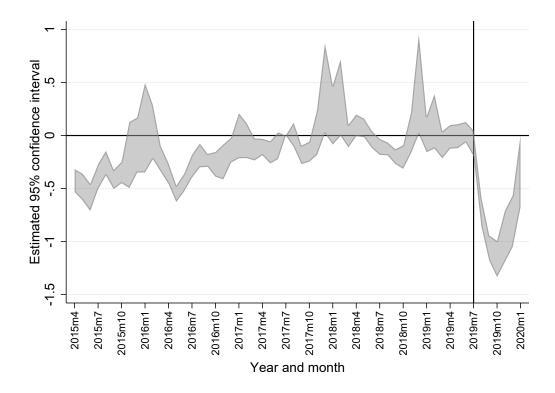
Notes: The CI is estimated from regression equation (7). Standard errors are clustered by country and time. The baseline level is set in July 2017.

Source: Authors' estimation, based on Overnight Travel Statistics Survey.

negative  $\chi_t$  from July 2019.

We first test the common trends assumption for this analysis and find that it does not hold. Similar to the results above using the Japanese data for accommodation services exports by country, we present the results using the Korean data for departures by country as a reference, not as a main result. Figure 7 plots the estimated 95 percent CI of  $\chi_t$ , setting July 2017 as the base level for the coefficients as before. We can confirm that the CI declined sharply from July 2019. The results suggest that the sharp drop of visitors from Korea to Japan is not attributable to an overall demand shock in Korea.

Figure 7: Number of Visitors from Korea to Japan Relative to Other Destination Countries: Korean Data



Notes: The CI is estimated from regression equation (8). Standard errors are clustered by country and time. The baseline level is set in July 2017.

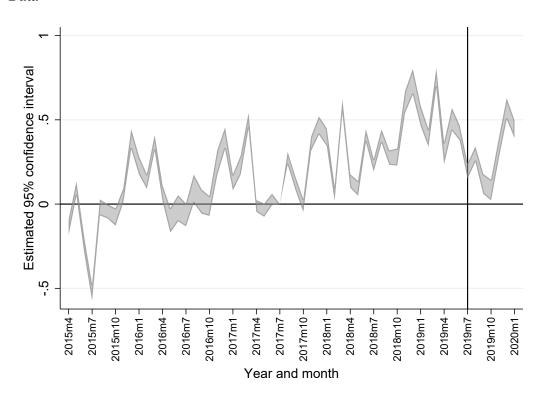
Source: Authors' estimation, based on data from the Korea Tourism Organization website.

It is also interesting to note that the Korean consumer boycott behavior does not seem to cause retaliation from Japanese consumers towards Korean travel. By replacing the dependent variable from the number of departures from Korea to that of arrivals to Korea in equation (8), we can examine the possibility of retaliation to the boycott. Again we find that the common trends assumption is not met for this analysis, so we present the results merely as a reference for the reader.<sup>47</sup> Figure 8 presents the estimation results where we focus on arrivals to Korea from Japan relative to other origin countries. The CI has been significantly positive since November 2017, indicating a stronger tendency for visitors to Korea to be from Japan. We do

<sup>&</sup>lt;sup>46</sup>Detailed results on the test of the common trends assumption are presented in Appendix D.

<sup>&</sup>lt;sup>47</sup>Detailed results on the test of the common trends assumption are presented in Appendix D.

Figure 8: Number of Visitors to Korea from Japan Relative to Other Origin Countries: Korean Data



Notes: The CI is estimated from regression equation (8) but using the log of the number of arrivals to Korea as the dependent variable. Standard errors are clustered by country and time. The baseline level is set in July 2017. Source: Authors' estimation, based on data from the Korea Tourism Organization website.

not find evidence that visitors from Japan to Korea decreased significantly after July 2019.

#### 6.4 Estimated revenue effects

Our empirical strategy in Sections 4 and 5 focused on estimating the causal effects of the Korean consumer boycott on the *quantity* of monthly exports of accommodation services from Japan to Korea. We turn now to a brief discussion of how our results can be utilized to estimate changes in annual export *revenues* by prefecture for 2019. To compute a monthly growth rate for prefectural revenues from accommodation services, we apply the following equation:

$$\frac{d(P_{it}Q_{it})}{(P_{it}Q_{it})} = \frac{Q_{it}dP_{it}}{(P_{it}Q_{it})} + \frac{P_{it}dQ_{it}}{(P_{it}Q_{it})} = \frac{dP_{it}}{P_{it}} + \frac{dQ_{it}}{Q_{it}},\tag{9}$$

where  $P_{it}$  and  $Q_{it}$  are prefecture i's price and quantity (i.e., visitor-nights) of accommodations in month t. Our aggregate-level analysis provides us with coefficients of  $(s_i \times \text{Post}_t)$  that can be used to calculate growth rates for quantities (i.e.,  $dQ_{it}/Q_{it}$ ), as shown in Table 8.<sup>48</sup> However, data is not available at the prefecture-month level for average prices of accommodations. The best available data is survey data at the annual-countrywide level that show that the average expenditure per person-night for Korean visitors fell from 15,954 JPY to 13,461 JPY between 2018 and 2019, while the corresponding value for all foreign visitors rose from 14,533 JPY to 15,598 JPY.<sup>49</sup> Since this annual data is insufficient for empirically testing for the existence of a causal link between these expenditure trend differentials and the consumer boycott, we adopt a conservative approach to estimating revenue changes by assuming that the boycott caused no changes in monthly aggregate-level prices of accommodations (i.e., assume  $dP_{it}/P_{it} = 0$ ).

The boycott effect is applicable for six months of 2019 (i.e., from July-December, 2019), so the average annual effect on visitor-night quantities is roughly estimated as half of our estimated monthly effect. By conservatively assuming no price changes due to the boycott, the average annual effect on quantities is then equivalent to the average annual effect on revenues, when both are expressed in growth rate terms. Table 10 shows these annual revenue growth rate effects for each prefecture in column (2). In this table, the prefectures again are ranked from highest to lowest in terms of Korea dependency and the annual number of visitor-nights for 2018 is shown in column (1) to provide an indication of the relative size of each prefecture's accommodation services industry. With the maximum Korea dependency ratio of 0.563, Oita prefecture suffers the largest boycott effect in terms of annual revenue growth rate with an estimated loss of 17.4 percent. At the opposite end of the spectrum, Yamanashi prefecture's Korea dependency ratio is only 0.015, so its estimated annual revenue loss is only 0.6 percent. The average prefecture loses an estimated 5.4 percent of accommodations services revenue in 2019 due to the boycott, while eight prefectures suffer losses of 10.0 percent or more. At the opposite end of the distribution, 14 prefectures lose less than 2.0 percent of their annual accommodations services revenues due to the boycott.

<sup>&</sup>lt;sup>48</sup>We use the mean of  $(s_i \times Post_t)$  coefficients from our two estimation methods and two sample periods that satisfy the common trends assumption, which is -0.75924.

<sup>&</sup>lt;sup>49</sup>The average expenditure per person-night data is from the Japan Tourism Agency's "Consumption Trend Survey for Foreigners Visiting Japan", available in Japanese. Note that the average expenditure data reflects spending on accommodations, food and drink, local transportation, etc. For convenience, we use the term "accommodation services revenues" to refer to revenues from accommodations and related travel services.

Table 10: Estimated Revenue Losses in 2019 Due to the Korean Consumer Boycott

Company			A	ggregate-level ar	nalysis
Prefecture         Share for 2015m4- 2018         Quantity in Est. annual growth rate in 2019 in JPY in 2019m6         Est. annual growth rate in 2019 in JPY in 2019m6           Oita         0.5627         1,057.7         -0.1738         -2,672,322           Saga         0.4965         372.5         -0.1570         -849,973           Yamaguchi         0.4548         90.7         -0.1460         -192,424           Fukuoka         0.4399         3,026.9         -0.1420         -6,245,227           Tottori         0.4042         138.7         -0.1321         -266,344           Miyazaki         0.4006         297.4         -0.1311         -566,760           Nagasaki         0.3266         512.1         -0.1098         -817,244           Kumamoto         0.3122         860.5         -0.1055         -1,319,576           Okinawa         0.2588         4,554.7         -0.0892         -5,904,172           Osaka         0.1788         11,637.6         -0.0635         -10,734,710           Kagoshima         0.1716         658.6         -0.0611         -584,621           Ehime         0.1698         190.9         -0.0605         -167,795           Hokkaido         0.1622         7,164.2				00 0	
Prefecture         Share for 2015m4- 2018 growth rate in 2019 in JPY         Est. annual growth rate in 2019 in JPY         Est. ch. For 2015m4- 2018 growth rate in 2019 in JPY           Oita         0.5627 1,057.7 -0.1738 -2,672,322         322.5 -0.1570 -0.1738 -2,672,322         323.2 -0.1570 -0.1460 -192,424         449.973           Yamaguchi         0.4548 90.7 -0.1460 -192,424         -1.0400 -1.0240 -6.245,227         -2.252,227           Tottori         0.4042 138.7 -0.1321 -2.66,344         -2.66,744           Miyazaki         0.4006 297.4 -0.1311 -566,760         -566,760           Nagasaki         0.3266 512.1 -0.1098 -817,244         -817,244           Kumamoto         0.3122 860.5 -0.1055 -1,319,576         -1,319,576           Okinawa         0.2588 4,554.7 -0.0892 -5,904,172         -5904,172           Osaka         0.1788 11,637.6 -0.0635 -10,734,710           Kagoshima         0.1716 658.6 -0.0611 -584,621           Ehime         0.1698 190.9 -0.0605 -167,795           Hokkaido         0.1622 7,164.2 -0.0579 -6,031,948           Aomori         0.1553 283.4 -0.0556 -229,007           Kagawa         0.1545 377.1 -0.0553 -303,305           Shimane         0.1515 54.9 -0.0543 -43,339           Hyogo         0.1281 1,074.5 -0.0463 -723,591           Saitama         0.1284 1,074.5 -0.0463 -723,591		Korea	Foreign	Foreign	` '
Prefecture         Share for 2015m4- 2018 growth rate 2019 in JPY         Est. annual square provided and provided shared					
2015m4- 2019m6         2018 in 2019         growth rate in 2019         2019 in JPY           Oita         0.5627         1,057.7         -0.1738         -2,672,322           Saga         0.4965         372.5         -0.1570         -849,973           Yamaguchi         0.4548         90.7         -0.1460         -192,424           Fukuoka         0.4399         3,026.9         -0.1420         -6,245,227           Tottori         0.4042         138.7         -0.1321         -266,344           Miyazaki         0.4006         297.4         -0.1311         -566,760           Nagasaki         0.3266         512.1         -0.1098         -817,244           Kumamoto         0.3122         860.5         -0.1055         -1,319,576           Okinawa         0.2588         4,554.7         -0.0892         -5,904,172           Osaka         0.1788         11,637.6         -0.0635         -10,734,710           Kagoshima         0.1716         658.6         -0.0611         -584,621           Ehime         0.1698         190.9         -0.0605         -167,795           Hokkaido         0.1622         7,164.2         -0.0579         -6,231,948           Aomori <td></td> <td>1 )</td> <td>O</td> <td></td> <td></td>		1 )	O		
2015m4- 2019m6         2018 in 2019         growth rate in 2019         2019 in JPY           Oita         0.5627         1,057.7         -0.1738         -2,672,322           Saga         0.4965         372.5         -0.1570         -849,973           Yamaguchi         0.4548         90.7         -0.1460         -192,424           Fukuoka         0.4399         3,026.9         -0.1420         -6,245,227           Tottori         0.4042         138.7         -0.1321         -266,344           Miyazaki         0.4006         297.4         -0.1311         -566,760           Nagasaki         0.3266         512.1         -0.1098         -817,244           Kumamoto         0.3122         860.5         -0.1055         -1,319,576           Okinawa         0.2588         4,554.7         -0.0892         -5,904,172           Osaka         0.1788         11,637.6         -0.0635         -10,734,710           Kagoshima         0.1716         658.6         -0.0611         -584,621           Ehime         0.1698         190.9         -0.0605         -167,795           Hokkaido         0.1622         7,164.2         -0.0579         -6,231,948           Aomori <td>Prefecture</td> <td>Share for</td> <td>Quantity in</td> <td>Est. annual</td> <td>Est. ch. For</td>	Prefecture	Share for	Quantity in	Est. annual	Est. ch. For
Oita         0.5627         1,057.7         -0.1738         -2,672,322           Saga         0.4965         372.5         -0.1570         -849,973           Yamaguchi         0.4548         90.7         -0.1460         -192,424           Fukuoka         0.4399         3,026.9         -0.1420         -6,245,227           Tottori         0.4042         138.7         -0.1321         -266,344           Miyazaki         0.4006         297.4         -0.1311         -566,760           Nagasaki         0.3266         512.1         -0.1098         -817,244           Kumamoto         0.3122         860.5         -0.1055         -1,319,576           Okinawa         0.2588         4,554.7         -0.0892         -5,904,172           Osaka         0.1788         11,637.6         -0.0635         -10,734,710           Kagoshima         0.1716         658.6         -0.0611         -584,621           Ehime         0.1698         190.9         -0.0605         -167,795           Hokkaido         0.1622         7,164.2         -0.0579         -6,031,948           Aomori         0.1553         283.4         -0.0533         -303,305           Shimane					2019 in JPY
Oita         0.5627         1,057.7         -0.1738         -2,672,322           Saga         0.4965         372.5         -0.1570         -849,973           Yamaguchi         0.4548         90.7         -0.1460         -192,424           Fukuoka         0.4399         3,026.9         -0.1420         -6,245,227           Tottori         0.4042         138.7         -0.1321         -266,344           Miyazaki         0.4006         297.4         -0.1311         -566,760           Nagasaki         0.3266         512.1         -0.1098         -817,244           Kumamoto         0.3122         860.5         -0.1055         -1,319,576           Okinawa         0.2588         4,554.7         -0.0892         -5,904,172           Osaka         0.1788         11,637.6         -0.0635         -10,734,710           Kagoshima         0.1716         658.6         -0.0611         -584,621           Ehime         0.1698         190.9         -0.0605         -167,795           Hokkaido         0.1622         7,164.2         -0.0579         -6,031,948           Aomori         0.1535         283.4         -0.0556         -229,007           Kagawa		2019m6		0	,
Saga         0.4965         372.5         -0.1570         -849,973           Yamaguchi         0.4548         90.7         -0.1460         -192,424           Fukuoka         0.4399         3,026.9         -0.1420         -6,245,227           Tottori         0.4042         138.7         -0.1321         -266,344           Miyazaki         0.4006         297.4         -0.1311         -566,760           Nagasaki         0.3266         512.1         -0.1098         -817,244           Kumamoto         0.3122         860.5         -0.1055         -1,319,576           Okinawa         0.2588         4,554.7         -0.0892         -5,904,172           Osaka         0.1788         11,637.6         -0.0635         -10,734,710           Kagoshima         0.1716         658.6         -0.0611         -584,621           Ehime         0.1698         190.9         -0.0605         -167,795           Hokkaido         0.1622         7,164.2         -0.0579         -6,031,948           Aomori         0.1533         283.4         -0.0556         -229,007           Kagawa         0.1545         377.1         -0.0553         -303,305           Shimane	Oita	0.5627	1,057.7		-2,672,322
Yamaguchi         0.4548         90.7         -0.1460         -192,424           Fukuoka         0.4399         3,026.9         -0.1420         -6,245,227           Tottori         0.4042         138.7         -0.1321         -266,344           Miyazaki         0.4006         297.4         -0.1311         -566,760           Nagasaki         0.3266         512.1         -0.1098         -817,244           Kumamoto         0.3122         860.5         -0.1055         -1,319,576           Okinawa         0.2588         4,554.7         -0.0892         -5,904,172           Osaka         0.1788         11,637.6         -0.0635         -10,734,710           Kagoshima         0.1716         658.6         -0.0611         -584,621           Ehime         0.1698         190.9         -0.0605         -167,795           Hokkaido         0.1622         7,164.2         -0.0579         -6,031,948           Aomori         0.1553         283.4         -0.0556         -229,007           Kagawa         0.1545         377.1         -0.0553         -303,305           Shimane         0.1515         54.9         -0.0543         -43,339           Akita					
Fukuoka         0.4399         3,026.9         -0.1420         -6,245,227           Tottori         0.4042         138.7         -0.1321         -266,344           Miyazaki         0.4006         297.4         -0.1311         -566,760           Nagasaki         0.3266         512.1         -0.1098         -817,244           Kumamoto         0.3122         860.5         -0.1055         -1,319,576           Okinawa         0.2588         4,554.7         -0.0892         -5,904,172           Osaka         0.1788         11,637.6         -0.0635         -10,734,710           Kagoshima         0.1716         658.6         -0.0611         -584,621           Ehime         0.1698         190.9         -0.0605         -167,795           Hokkaido         0.1622         7,164.2         -0.0579         -6,031,948           Aomori         0.1553         283.4         -0.0556         -229,007           Kagawa         0.1545         377.1         -0.0553         -303,305           Shimane         0.1515         54.9         -0.0543         -43,339           Akita         0.1396         99.9         -0.0503         -722,996           Hyogo         <			90.7		
Tottori 0.4042 138.7 -0.1321 -266,344 Miyazaki 0.4006 297.4 -0.1311 -566,760 Nagasaki 0.3266 512.1 -0.1098 -817,244 Kumamoto 0.3122 860.5 -0.1055 -1,319,576 Okinawa 0.2588 4,554.7 -0.0892 -5,904,172 Osaka 0.1788 11,637.6 -0.0635 -10,734,710 Kagoshima 0.1716 658.6 -0.0611 -584,621 Ehime 0.1698 190.9 -0.0605 -167,795 Hokkaido 0.1622 7,164.2 -0.0579 -6,031,948 Aomori 0.1553 283.4 -0.0556 -229,007 Kagawa 0.1545 377.1 -0.0553 -303,305 Shimane 0.1515 54.9 -0.0543 -43,339 Akita 0.1396 99.9 -0.0503 -72,996 Hyogo 0.1281 1,074.5 -0.0463 -723,591 Saitama 0.1254 140.8 -0.0454 -92,891 Mie 0.1168 290.3 -0.0424 -179,006 Shiga 0.1130 380.3 -0.0411 -227,185 Yamagata 0.1092 117.8 -0.0398 -68,096 Toyama 0.1028 405.9 -0.0370 -32,766 Niigata 0.0067 260.3 -0.0370 -32,766 Niigata 0.0075 19,258.8 -0.0279 -7,806,436 Ibaraki 0.0752 45.9 -0.0253 -32,7894 Tokyo 0.0756 19,258.8 -0.0279 -7,806,436 Ibaraki 0.0715 162.8 -0.0264 -62,504 Wakayama 0.0653 12.1 -0.0242 -42,546 Iwate 0.0637 236.7 -0.0236 -81,192 Kanagawa 0.0572 24,39.4 -0.0255 -82,953 Fukushima 0.0512 2,439.4 -0.0191 -675,858 Tokyo 0.0522 4,506.3 -0.0191 -675,858 Tokyo 0.0522 4,506.3 -0.0191 -675,858 Tokyohima 0.0512 2,439.4 -0.0191 -675,858 Tokushima 0.0697 77.7 -0.0185 -20,908				-0.1420	
Miyazaki         0.4006         297.4         -0.1311         -566,760           Nagasaki         0.3266         512.1         -0.1098         -817,244           Kumamoto         0.3122         860.5         -0.1055         -1,319,576           Okinawa         0.2588         4,554.7         -0.0892         -5,904,172           Osaka         0.1788         11,637.6         -0.0635         -10,734,710           Kagoshima         0.1716         658.6         -0.0611         -584,621           Ehime         0.1698         190.9         -0.0605         -167,795           Hokkaido         0.1622         7,164.2         -0.0579         -6,031,948           Aomori         0.1553         283.4         -0.0556         -229,007           Kagawa         0.1545         377.1         -0.0553         -303,305           Shimane         0.1515         54.9         -0.0543         -43,339           Akita         0.1396         99.9         -0.0503         -72,996           Hyogo         0.1281         1,074.5         -0.0463         -723,591           Saitama         0.1254         140.8         -0.0454         -92,891           Mie         0.116	Tottori				
Nagasaki         0.3266         512.1         -0.1098         -817,244           Kumamoto         0.3122         860.5         -0.1055         -1,319,576           Okinawa         0.2588         4,554.7         -0.0892         -5,904,172           Osaka         0.1788         11,637.6         -0.0635         -10,734,710           Kagoshima         0.1716         658.6         -0.0611         -584,621           Ehime         0.1698         190.9         -0.0605         -167,795           Hokkaido         0.1622         7,164.2         -0.0579         -6,031,948           Aomori         0.1553         283.4         -0.0556         -229,007           Kagawa         0.1545         377.1         -0.0553         -303,305           Shimane         0.1515         54.9         -0.0543         -43,339           Akita         0.1396         99.9         -0.0503         -72,996           Hyogo         0.1281         1,074.5         -0.0463         -723,591           Saitama         0.1254         140.8         -0.0454         -92,891           Mie         0.1168         290.3         -0.0424         -179,006           Shiga         0.1130 </td <td>Miyazaki</td> <td></td> <td></td> <td></td> <td></td>	Miyazaki				
Kumamoto         0.3122         860.5         -0.1055         -1,319,576           Okinawa         0.2588         4,554.7         -0.0892         -5,904,172           Osaka         0.1788         11,637.6         -0.0635         -10,734,710           Kagoshima         0.1716         658.6         -0.0611         -584,621           Ehime         0.1698         190.9         -0.0605         -167,795           Hokkaido         0.1622         7,164.2         -0.0579         -6,031,948           Aomori         0.1553         283.4         -0.0556         -229,007           Kagawa         0.1545         377.1         -0.0553         -303,305           Shimane         0.1515         54.9         -0.0543         -43,339           Akita         0.1396         99.9         -0.0503         -72,996           Hyogo         0.1281         1,074.5         -0.0463         -723,591           Saitama         0.1254         140.8         -0.0454         -92,891           Mie         0.1168         290.3         -0.0424         -179,006           Shiga         0.1130         380.3         -0.0411         -227,185           Yamagata         0.1092 </td <td></td> <td></td> <td></td> <td></td> <td></td>					
Okinawa         0.2588         4,554.7         -0.0892         -5,904,172           Osaka         0.1788         11,637.6         -0.0635         -10,734,710           Kagoshima         0.1716         658.6         -0.0611         -584,621           Ehime         0.1698         190.9         -0.0605         -167,795           Hokkaido         0.1622         7,164.2         -0.0579         -6,031,948           Aomori         0.1553         283.4         -0.0556         -229,007           Kagawa         0.1545         377.1         -0.0553         -303,305           Shimane         0.1515         54.9         -0.0543         -43,339           Akita         0.1396         99.9         -0.0503         -72,996           Hyogo         0.1281         1,074.5         -0.0463         -723,591           Saitama         0.1254         140.8         -0.0454         -92,891           Mie         0.1168         290.3         -0.0424         -179,006           Shiga         0.1130         380.3         -0.0411         -227,185           Yamagata         0.1092         117.8         -0.0398         -68,096           Toyama         0.1034					
Osaka         0.1788         11,637.6         -0.0635         -10,734,710           Kagoshima         0.1716         658.6         -0.0611         -584,621           Ehime         0.1698         190.9         -0.0605         -167,795           Hokkaido         0.1622         7,164.2         -0.0579         -6,031,948           Aomori         0.1553         283.4         -0.0556         -229,007           Kagawa         0.1545         377.1         -0.0553         -303,305           Shimane         0.1515         54.9         -0.0543         -43,339           Akita         0.1396         99.9         -0.0503         -72,996           Hyogo         0.1281         1,074.5         -0.0463         -723,591           Saitama         0.1254         140.8         -0.0454         -92,891           Mie         0.1168         290.3         -0.0424         -179,006           Shiga         0.1130         380.3         -0.0411         -227,185           Yamagata         0.1092         117.8         -0.0398         -68,096           Toyama         0.1034         235.3         -0.0376         -221,441           Kochi         0.1012					
Kagoshima         0.1716         658.6         -0.0611         -584,621           Ehime         0.1698         190.9         -0.0605         -167,795           Hokkaido         0.1622         7,164.2         -0.0579         -6,031,948           Aomori         0.1553         283.4         -0.0556         -229,007           Kagawa         0.1545         377.1         -0.0553         -303,305           Shimane         0.1515         54.9         -0.0543         -43,339           Akita         0.1396         99.9         -0.0503         -72,996           Hyogo         0.1281         1,074.5         -0.0463         -723,591           Saitama         0.1254         140.8         -0.0454         -92,891           Mie         0.1168         290.3         -0.0424         -179,006           Shiga         0.1130         380.3         -0.0411         -227,185           Yamagata         0.1092         117.8         -0.0398         -68,096           Toyama         0.1034         235.3         -0.0378         -129,101           Okayama         0.1028         405.9         -0.0375         -221,441           Kochi         0.1012 <td< td=""><td></td><td></td><td></td><td></td><td></td></td<>					
Ehime         0.1698         190.9         -0.0605         -167,795           Hokkaido         0.1622         7,164.2         -0.0579         -6,031,948           Aomori         0.1553         283.4         -0.0556         -229,007           Kagawa         0.1545         377.1         -0.0553         -303,305           Shimane         0.1515         54.9         -0.0543         -43,339           Akita         0.1396         99.9         -0.0503         -72,996           Hyogo         0.1281         1,074.5         -0.0463         -723,591           Saitama         0.1254         140.8         -0.0454         -92,891           Mie         0.1168         290.3         -0.0424         -179,006           Shiga         0.1130         380.3         -0.0411         -227,185           Yamagata         0.1092         117.8         -0.0398         -68,096           Toyama         0.1034         235.3         -0.0378         -129,101           Okayama         0.1028         405.9         -0.0375         -221,441           Kochi         0.1012         61.0         -0.0370         -32,766           Niigata         0.0967         260					
Hokkaido         0.1622         7,164.2         -0.0579         -6,031,948           Aomori         0.1553         283.4         -0.0556         -229,007           Kagawa         0.1545         377.1         -0.0553         -303,305           Shimane         0.1515         54.9         -0.0543         -43,339           Akita         0.1396         99.9         -0.0503         -72,996           Hyogo         0.1281         1,074.5         -0.0463         -723,591           Saitama         0.1254         140.8         -0.0454         -92,891           Mie         0.1168         290.3         -0.0424         -179,006           Shiga         0.1130         380.3         -0.0411         -227,185           Yamagata         0.1092         117.8         -0.0398         -68,096           Toyama         0.1034         235.3         -0.0378         -129,101           Okayama         0.1028         405.9         -0.0375         -221,441           Kochi         0.1012         61.0         -0.0375         -221,441           Kochi         0.1012         61.0         -0.0370         -32,766           Niigata         0.0967         260.	0				
Aomori         0.1553         283.4         -0.0556         -229,007           Kagawa         0.1545         377.1         -0.0553         -303,305           Shimane         0.1515         54.9         -0.0543         -43,339           Akita         0.1396         99.9         -0.0503         -72,996           Hyogo         0.1281         1,074.5         -0.0463         -723,591           Saitama         0.1254         140.8         -0.0454         -92,891           Mie         0.1168         290.3         -0.0424         -179,006           Shiga         0.1130         380.3         -0.0411         -227,185           Yamagata         0.1092         117.8         -0.0398         -68,096           Toyama         0.1034         235.3         -0.0378         -129,101           Okayama         0.1028         405.9         -0.0375         -221,441           Kochi         0.1012         61.0         -0.0375         -221,441           Kochi         0.1012         61.0         -0.0370         -32,766           Niigata         0.0967         260.3         -0.0354         -133,884           Tokyo         0.0756         19,258.8 <td></td> <td></td> <td></td> <td></td> <td></td>					
Kagawa         0.1545         377.1         -0.0553         -303,305           Shimane         0.1515         54.9         -0.0543         -43,339           Akita         0.1396         99.9         -0.0503         -72,996           Hyogo         0.1281         1,074.5         -0.0463         -723,591           Saitama         0.1254         140.8         -0.0454         -92,891           Mie         0.1168         290.3         -0.0424         -179,006           Shiga         0.1130         380.3         -0.0411         -227,185           Yamagata         0.1092         117.8         -0.0398         -68,096           Toyama         0.1034         235.3         -0.0378         -129,101           Okayama         0.1028         405.9         -0.0375         -221,441           Kochi         0.1012         61.0         -0.0370         -32,766           Niigata         0.0967         260.3         -0.0354         -133,884           Tokyo         0.0756         19,258.8         -0.0279         -7,806,436           Ibaraki         0.0715         162.8         -0.0264         -62,504           Wakayama         0.0691         35					
Shimane         0.1515         54.9         -0.0543         -43,339           Akita         0.1396         99.9         -0.0503         -72,996           Hyogo         0.1281         1,074.5         -0.0463         -723,591           Saitama         0.1254         140.8         -0.0454         -92,891           Mie         0.1168         290.3         -0.0424         -179,006           Shiga         0.1130         380.3         -0.0411         -227,185           Yamagata         0.1092         117.8         -0.0398         -68,096           Toyama         0.1034         235.3         -0.0378         -129,101           Okayama         0.1028         405.9         -0.0375         -221,441           Kochi         0.1012         61.0         -0.0370         -32,766           Niigata         0.0967         260.3         -0.0354         -133,884           Tokyo         0.0756         19,258.8         -0.0279         -7,806,436           Ibaraki         0.0715         162.8         -0.0264         -62,504           Wakayama         0.0691         359.4         -0.0256         -133,474           Tochigi         0.0684         2					
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Toyama         0.1034         235.3         -0.0378         -129,101           Okayama         0.1028         405.9         -0.0375         -221,441           Kochi         0.1012         61.0         -0.0370         -32,766           Niigata         0.0967         260.3         -0.0354         -133,884           Tokyo         0.0756         19,258.8         -0.0279         -7,806,436           Ibaraki         0.0715         162.8         -0.0264         -62,504           Wakayama         0.0691         359.4         -0.0256         -133,474           Tochigi         0.0684         225.6         -0.0253         -82,953           Fukushima         0.0653         121.1         -0.0242         -42,546           Iwate         0.0637         236.7         -0.0236         -81,192           Kanagawa         0.0573         2,130.2         -0.0213         -658,984           Kyoto         0.0522         4,506.3         -0.0194         -1,272,398           Aichi         0.0512         2,439.4         -0.0191         -675,853           Fukui         0.0512         57.7         -0.0191         -15,986           Tokushima         0.0497					
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Aichi       0.0512       2,439.4       -0.0191       -675,853         Fukui       0.0512       57.7       -0.0191       -15,986         Tokushima       0.0497       77.7       -0.0185       -20,908	Kvoto				
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Hiroshima 0.0467 731.0 -0.0174 -185,044					
Gumma 0.0463 255.1 -0.0173 -64,038					
Gifu 0.0437 1,063.1 -0.0163 -252,112					
Nagano 0.0424 1,043.1 -0.0158 -240,119					
Chiba 0.0414 3,652.3 -0.0155 -821,224					
Ishikawa 0.0403 725.8 -0.0151 -158,917					
Shizuoka 0.0400 1,460.1 -0.0150 -317,365					
Yamanashi 0.0145 1,506.6 -0.0055 -119,861					
Mean 0.1494 1,595.3 -0.0536 -1,243,154					
Total 74,979.3 -51,982,790			,		

Notes: Foreign visitor-nights reflect total for 20 countries used in estimation (unit: 1,000 person-nights). The unit for revenue is 1,000 JPY. Est. ch. = estimated change. Revenue change in (3) = (1)  $\times$  (14,533 JPY)  $\times$  (2), with small discrepancies due to rounding off of displayed values.

Source: Authors' estimation, based on Overnight Travel Statistics Survey.

Column (3) of Table 10 uses the growth rates in column (2) and the prefectures' total accommodations revenues from 2018 to estimate the nominal revenues lost in 2019 due to the boycott. The top three prefectures for boycott-induced accommodation revenue losses are Osaka, Tokyo and Fukuoka with estimated losses of 10.7 billion JPY, 7.8 billion JPY and 6.2 billion JPY, respectively. Across all prefectures, our conservative estimate of accommodation revenue losses caused by the boycott is 52.0 billion JPY (or approximately 476.9 million USD). If the boycott-induced travel cancellations by Koreans caused hotels in Japan to discount their rooms and/or caused a shift in Korean visitors away from higher-spending travelers and towards lower-spending travelers, then our estimates of revenue changes based on quantity changes alone is a lower bound for the real effect on accommodation revenues. Second commodation revenues.

While acknowledging that the export revenue losses are roughly estimated, the large range in estimated loss ratios across prefectures, from less than one percent to over 17 percent, demonstrates again the importance of considering regional heterogeneity in examining the impacts of a consumer boycott. It is also important to note that our focus on the regional impacts of the Korean consumer boycott on accommodation services in Japan does not include the negative direct impacts on Korean airlines and travel agencies, nor the indirect effects on other businesses in Korea that benefit from Korean travel to Japan.<sup>53</sup>

## 7 Concluding Remarks

Political conflict impacts international trade not only through trade policy but also through consumer boycotts. In light of increasing concerns regarding political conflict and regional inequality, we present the first study of the heterogeneous impacts of a boycott across regions within a boycotted country.<sup>54</sup> We investigate the recent Korean consumer boycott activity from July 2019 in response to Japan's restrictions on exports of semiconductor materials and display panels considered vital to Korea's technology industry. Using prefecture-month foreign visitor data in Japan between April 2015 and January 2020, we employ difference-in-difference-in-differences (DDD) and difference-in-differences (DID) designs.

Estimation results indicate that the impact of the Korean consumer boycott is heterogeneous across prefectures within Japan, which is consistent with the diversification story and with the hypothesis that Korean tourists were the most likely participants in the consumer

<sup>&</sup>lt;sup>50</sup>The average expenditure per person-night for all foreign tourists in 2018 (i.e., 14,533 JPY) is used along with visitor-night quantities to calculate total revenues per prefecture for 2018.

<sup>&</sup>lt;sup>51</sup>An average exchange rate for 2019 of 109 JPY/USD is used.

<sup>&</sup>lt;sup>52</sup>Note that Inada, Irie and Shimoda (2019) use input-output analysis to estimate that Osaka prefecture lost 27 billion JPY in terms of value-added due to the Korean travel boycott. Our finding that Osaka prefecture loses 10.7 billion JPY is similar in magnitude but not directly comparable to their estimate because: 1) we focus on revenues rather than value-added, 2) their estimate is based on a traditional input-output analysis, and 3) they take into account inter-industry linkages while we do not with our conservative estimates.

<sup>&</sup>lt;sup>53</sup>Japan Tourism Agency (2019) reports that travel to Japan (either personally or by family member or acquaintance) motivated about 50 percent of those purchasing Japanese food and beverage products overseas. The other options for motivations were "information and articles on travel to Japan", "TV programs and special articles on travel to Japan", and "other". The overseas questionnaire survey was conducted in February, 2019.

<sup>&</sup>lt;sup>54</sup>Note that regional heterogeneity in the impacts of political conflict is addressed by Che, Du, Lu and Tao (2015), but their research does not involve a consumer boycott. They examine the heterogeneous long-run impacts of Japan's invasion of China from 1937 to 1945 and find that Chinese regions that suffered larger civilian casualties during the invasion have lower trade with and investment from Japan in 2001.

boycott. For prefectures with high (i.e., 75th percentile) pre-boycott dependency on Korean visitors, the negative impact on exports of accommodation services to Korea is about 9.1 to 11.1 percentage points larger than that for prefectures with low (i.e., 25th percentile) dependency, with export losses of 56.9 to 60.9 percent and 47.8 to 49.7 percent, respectively. These negative impacts on prefectural exports to Korea are too large to be offset by increases in exports to other countries. As a result, Japanese prefectures had net adverse effects from the boycott, with a 10.5 to 13.3 percent decline in total exports of accommodation service for high Korea dependency prefectures and a corresponding decline of 3.3 to 4.2 percent for low Korea dependency prefectures. These ranges of boycott effects summarize our results in using two estimation models and two sample periods to identify estimated bands for the boycott effects that are reassuringly narrow for a specific quartile prefecture, heterogeneous across prefectures and robust to the exclusion of outliers. Our main message holds even when we use an alternative measure of diversification.

Our results have important policy implications. While the Japan–Korea political conflict was sparked by actions taken by the countries' national leaders and the ensuing Korean consumer boycott targeted Japanese services (and products) nationwide, the impacts of the boycott are not spread equally throughout Japan. We conservatively estimate that the average prefecture loses 5.4 percent of its annual revenue from accommodations exports in 2019 due to the boycott but that single estimate obscures prefectural heterogeneity in outcomes. Eight prefectures suffer annual accommodations export revenue losses of more than 10 percent while 14 prefectures suffer losses of less than 2 percent. These disparate outcomes may contribute to increased inequality between regions. Therefore it is important for policy makers to take into account such regional impacts as a consequence of political conflict at the national level. To make regions less vulnerable to a foreign consumer boycott, travel promotion policies should target visitors with more diverse travel purposes and from more diverse countries of origin.

Before closing this study, we point out several pathways for future research. First, extending the analysis to a general equilibrium framework is an important avenue for future research. For example, our analysis did not take into account the potential substitution between Korean and domestic (i.e., Japanese) visitors. A general equilibrium analysis will allow us to quantify the full impact of the boycott, including welfare effects in Japan and Korea, more precisely. Second, it is also important to ask whether the impact of the consumer boycott is short- or long-lived. Due to the coronavirus pandemic, our analysis was not able to address this issue but we do find significant "angry consumer" effects that persisted at least for seven months in this case. Analysis of another boycott may enable us to pursue the issue of boycott longevity. Finally, it is also interesting to investigate the effect of the boycott, or more generally political conflict, on regional economic outcomes. Although regional outcomes such as GDP and employment are not available on a prefecture-month basis in Japan as of today, the construction of more detailed regional outcome data will help us to calculate the overall impact of the tourism decline on the regional and/or national economy by incorporating the share of tourism as part of the overall GDP. This would allow us to address an interesting political economy question as the policies that lead to international conflict are made at the national level but have very diverse regional impacts. We include these issues in our future research agenda.

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## **Appendices for Online Publication Only**

#### A Alternative Estimation Method: PPML Details

PPML estimation specifies the regression equation as the cross product between the exponential of the set of independent variables and the error term. For example, for the case of the disaggregate-level analysis (i.e., equation (1)), the regression equation is written as follows:

$$Y_{ijt} = \exp \left[\alpha + \psi_i + \psi_j + \psi_t + \beta_1(s_i \times \text{Post}_t) + \beta_2(s_i \times \text{KOR}_j) + \beta_3(\text{KOR}_j \times \text{Post}_t) + \gamma(s_i \times \text{KOR}_j \times \text{Post}_t)\right] \times \varepsilon_{ijt},$$
(A1)

where the variables are the same as before except for  $Y_{ijt}$  which is the actual (not log) value. Thus, this specification includes observations of zero exports. The aggregate-level analysis in equation (3) is rewritten in a similar manner so that both analyses can be estimated using PPML.

Table A1 presents the estimation results.<sup>55</sup> Columns (1)–(2) correspond with the disaggregate analysis of equation (1) while columns (3)–(4) apply the strictest possible model specification for our disaggregate analysis. Columns (5)–(6) correspond with the aggregate analysis of equation (3). There are two notable findings. First, the number of observations is the same as that of the log-linearized specification for columns (5)–(6) while it is different for columns (1)–(4). Thus there are no observations with zero trade for the aggregate-level analysis whereas there are some observations with zero trade for the disaggregated-level analysis. The shares of observations with zero trade are very small: 3.0 and 1.6 percent for the full- and medium-period samples, respectively. Second, although the coefficients are slightly different, the signs and significance levels of the coefficients are quite similar to those of the log-linearized specification.<sup>56</sup>

Table A2 uses the coefficients from PPML estimation for our disaggregate-level analysis, shown in columns (1)–(2) of Table A1, to calculate total magnitude effects of the boycott. These effects measure the losses in prefectural exports to Korea due to the boycott. The estimated export losses at the mean and at each quartile of the  $s_i$  distribution are shown in Table A2 and are used, along with those shown in Table 4, to create summary Tables A4 and 9.

Table A3 uses the coefficients from PPML estimation for our aggregate-level analysis, shown in columns (5)–(6) of Table A1, to calculate total magnitude effects of the boycott. These effects measure the losses in prefectural total exports due to the boycott. The estimated export losses at the mean and at each quartile of the  $s_i$  distribution are shown in Table A3 and are used, along with those shown in Table 8, to create summary Tables A4 and 9.

To facilitate a comparison between our main (log linear) and alternative (PPML) estimation methods, we present side-by-side comparisons of estimated boycott impacts in Table A4. This table merely summarizes the growth rate estimates from Tables 4, 8, A2, and A3. The disaggregate-level growth rates are within a tight range of -1.9 to 4.0 percentage points from our main specification (log linear) results and the aggregate-level growth rates are within an even tighter range of 0.4 to 1.8 percentage points from our main specification (log linear) results, as shown in Table A4. Thus, our results are robust to an alternative estimation method.

 $<sup>^{55}</sup>$ Following Santos Silva, Tenreyro, and Windmeijer (2015), we compute  $R^2$  as the square of the correlation between the dependent variable and the estimated conditional mean. Multi-way clustered standard errors are computed by the stata command ppmlhdfe developed by Correia, Guimarães, and Zylkin (2020).

<sup>&</sup>lt;sup>56</sup>Note that our coefficient of  $(s_i \times KOR_j \times Post_t)$  is even larger in (absolute value) magnitude in our robustness check using prefecture-time, country-time and prefecture-country fixed effects, but we use the coefficient values from our main specification to compute growth rates because we need a coefficient for  $(KOR_j \times Post_t)$  for this computation.

Table A1: Regression Results: Alternative Estimation Model

	D	isggregate-	level analys	sis	Aggregate-	level analysis
	(1)	(2)	(3)	(4)	(5)	(6)
Period	2015m4	2018m7	2015m4	2018m7	2015m4	2018m7
	-2020m1	-2020m1	-2020m1	-2020m1	-2020m1	-2020m1
$s_i \times \mathrm{Post}_t$	0.159***	0.302***			-0.766***	-0.655***
	[0.045]	[0.022]			[0.232]	[0.212]
$s_i \times KOR_j$	6.547***	6.516***				
•	[0.857]	[0.842]				
$KOR_j \times Post_t$	-0.613***	-0.618***				
	[0.097]	[0.072]				
$s_i \times \text{KOR}_j \times \text{Post}_t$	-1.346***	-1.368***	-1.725***	-1.618***		
	[0.139]	[0.116]	[0.418]	[0.395]		
Fixed effect						
Prefecture ( $\psi_i$ )	Yes	Yes	No	No	Yes	Yes
Country $(\psi_j)$	Yes	Yes	No	No	NA	NA
Time $(\psi_t)$	Yes	Yes	No	No	Yes	Yes
Prefecture-time ( $\psi_{it}$ )	No	No	Yes	Yes	NA	NA
Country-time $(\psi_{jt})$	No	No	Yes	Yes	NA	NA
Prefecture-country $(\psi_{ij})$	No	No	Yes	Yes	NA	NA
N	54,520	17,860	54,520	17,860	2,726	893
$R^2$	0.245	0.234	0.485	0.475	0.542	0.555

Notes: The PPML is employed for the estimation. Figures in brackets indicate standard errors clustered by prefecture, country, and time for columns (1)–(4) and by prefecture and time for columns (5)–(6). \*\*\* indicates the significance level at 1 percent. NA stands for not applicable.

Table A2: Impact of the Boycott on Prefectures' Exports to Korea: PPML Estimates

	(1)	(2)	(3)	(4)	(5)
			$(=(1)\times(2))$	(=(3) + KP Coeff.)	Total magnitude
Percentile	Coefficient	$s_i$	Relative magnitude	Total magnitude	converted
			(log change)	(log change)	(growth rate)
2015m4-2020	0m1				
Mean	-1.346	0.149	-0.201	-0.814	-0.557
25%	-1.346	0.051	-0.069	-0.682	-0.494
50%	-1.346	0.103	-0.138	-0.751	-0.528
75%	-1.346	0.170	-0.229	-0.842	-0.569
75-25% gap					-0.075
2018m7-2020	0m1				
Mean	-1.368	0.149	-0.204	-0.822	-0.561
25%	-1.368	0.051	-0.070	-0.688	-0.497
50%	-1.368	0.103	-0.141	-0.759	-0.532
75%	-1.368	0.170	-0.232	-0.850	-0.573
75-25% gap					-0.075

Notes: Exports to Korea mean the exports of accommodation services to Korea that are defined as the number of visitors from Korea (the total number of visitors who reside in Korea  $\times$  the number of nights stayed in Japan). Percentile indicates the quartiles of  $s_i$ . Coefficients are obtained from Table A1 and KP Coeff. means (KOR $_j \times \text{Post}_t$ ) coefficient from the corresponding sample period. Rounding off of displayed numbers explains small variations in calculated numbers shown above. Growth rate =  $\exp(\log \text{change}) - 1$ .

Source: Authors' estimation, based on Overnight Travel Statistics Survey.

Table A3: Impact of the Boycott on Prefectures' Total Exports: PPML Estimates

	(1)	(2)	(3)	(4)
			$(=(1) \times (2))$	Total magnitude
Percentile	Coefficient	$s_i$	Total magnitude	converted
			(log change)	(growth rate)
2015m4-2020	0m1			
Mean	-0.766	0.149	-0.114	-0.108
25%	-0.766	0.051	-0.039	-0.038
50%	-0.766	0.103	-0.079	-0.076
75%	-0.766	0.170	-0.130	-0.122
75-25% gap				-0.084
2018m7-2020	0m1			
Mean	-0.655	0.149	-0.098	-0.093
25%	-0.655	0.051	-0.034	-0.033
50%	-0.655	0.103	-0.067	-0.065
75%	-0.655	0.170	-0.111	-0.105
75-25% gap				-0.072

Notes: Exports mean the exports of accommodation services that are defined as the number of foreign visitors (the total number of visitors who reside outside Japan  $\times$  the number of nights stayed in Japan). Percentile indicates the quartiles of  $s_i$ . Coefficients are obtained from Table A1. Rounding off of displayed numbers explains small variations in calculated numbers shown above. Growth rate =  $\exp(\log \operatorname{change}) - 1$ .

Table A4: Comparison of Log Linear and PPML Estimates of Boycott Impacts

			el analysis			l analysis
	(1)	(2)	(3)	$\phantom{aaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaaa$	(5)	(6)
			(=(2)-(1))			(=(5)-(4))
	Log-linear	PPML	Difference	Log-linear	PPML	Difference
2015m	4–2020m1					
Mean	-0.590	-0.557	0.033	-0.118	-0.108	0.010
25%	-0.488	-0.494	-0.006	-0.042	-0.038	0.004
50%	-0.544	-0.528	0.016	-0.083	-0.076	0.007
75%	-0.609	-0.569	0.040	-0.133	-0.122	0.011
2018m	7–2020m1					
Mean	-0.587	-0.561	0.026	-0.109	-0.093	0.016
25%	-0.478	-0.497	-0.019	-0.039	-0.033	0.006
50%	-0.538	-0.532	0.006	-0.077	-0.065	0.012
75%	-0.606	-0.573	0.033	-0.123	-0.105	0.018
Max			0.040			0.018
Min			-0.019			0.004

Notes: Growth rates from log linear (PPML) estimation are obtained from Table 4 (A2) for the disaggregate-level analysis and from Table 8 (A3) for the aggregate-level analysis. Differences measure the percentage point difference in growth rates across the two estimation methods. Rounding off of displayed numbers explains small variations in calculated numbers shown above.

### **B** Alternative measure of diversification

One may suggest that we use a different measure of diversification because each prefecture's dependency ratio on Korean visitors,  $s_i$ , focuses on the concentration of exports to Korea alone. Therefore, the dependency ratio does not take into account the export diversification to other countries. One of the most frequently used measures of the diversification of exports is the Herfindahl index. Following Cadot, Carrère, and Strauss-Kahn (2011), we measure export diversification using the Herfindahl index  $h_i$  as follows:

$$h_i = \frac{\sum_j s_{ij}^2 - 1/n}{1 - 1/n},\tag{B1}$$

where  $s_{ij}$  is the average share of visitors from country j to total visitors from foreign countries in prefecture i before the boycott; n is the number of countries, which consists of 20 countries and the rest of the world (i.e., n=21). The Herfindahl index takes a value between 0 and 1, where 0 would indicate the most diverse export destination profile while 1 would indicate the least diverse profile. We estimate our regression equations, replacing  $s_i$  with  $h_i$  in equations (1)–(4).

Let us first check the common trends assumption. Table B1 presents the regression results. Columns (1)–(3) and (4)–(6) are the results for disaggregate- and aggregate-level analyses, respectively. Columns (1) and (4) are the results for the full-period sample, Columns (2) and (5) are the results for the medium-period sample, and columns (3) and (6) are the results for the short-period sample. Except for the full-sample in the disaggregate-level analysis in column (1), all of the coefficients are insignificant. The results generally support the validity of the common trends assumption. As for the disaggregate-level analysis, we present the results for the full-period sample as a reference.

Table B1: Common Trends Assumption: Alternative Diversification Measure

Table bi. Common fields Assumption. Alternative Diversification weasure							
	Disggre	Disggregate-level analysis			Aggre	gate-level a	nalysis
	(1)	(2)	(3)		(4)	(5)	(6)
Period	2015m4	2018m7	2019m1		2015m4	2018m7	2019m1
	-2019m6	-2019m6	-2019m6		-2019m6	-2019m6	-2019m6
$h_i \times \mathrm{Trend}_t$	Yes	Yes	Yes		-0.005	-0.001	-0.089
					[0.015]	[0.025]	[0.191]
$h_i \times KOR_j \times Trend_t$	0.025***	0.042	-0.325				
•	[0.005]	[0.087]	[0.177]				
Fixed effect							
Prefecture $(\psi_i)$	Yes	Yes	Yes		Yes	Yes	Yes
Country $(\psi_j)$	Yes	Yes	Yes		NA	NA	NA
Time $(\psi_t)$	Yes	Yes	Yes		Yes	Yes	Yes
$h_i \times KOR_j$	Yes	Yes	Yes		NA	NA	NA
$KOR_j \times Trend_t$	Yes	Yes	Yes		NA	NA	NA
$\overline{N}$	46,380	11,074	5,538		2,397	564	282
$R^2$	0.84	0.85	0.85		0.97	0.98	0.98

Notes: Figures in brackets indicate standard errors clustered by prefecture, country, and time for columns (1)–(3) and by prefecture and time for columns (4)–(6). \*\*\* indicates the significance level at 1 percent. NA stands for not applicable.

Source: Authors' estimation, based on Overnight Travel Statistics Survey.

Table B2 presents the DDD and DID estimation results. Columns (1)–(3) and (4)–(6) are the estimation results for disaggregate- and aggregate-level analyses, respectively. There are

two notable findings in this table. First, for the disaggregate-level analysis, the coefficients of  $(h_i \times \text{KOR}_j \times \text{Post}_t)$  are significantly negative for all three sample periods.<sup>57</sup> The results imply that the impact of the boycott on exports to Korea is heterogeneous across prefectures even when we measure export diversification by the Herfindahl index. Prefectures with more concentrated (i.e., less diverse) export portfolios suffer larger losses in exports to Korea due to the boycott. This result is consistent with the diversification story.

Table B2: Regression Results: Alternative Diversification Measure

	Disggregate-level analysis			Aggre	gate-level a	nalysis
	(1)	(2)	(3)	(4)	(5)	(6)
Period	2015m4	2018m7	2019m1	2015m4	2018m7	2019m1
	-2020m1	-2020m1	-2020m1	-2020m1	-2020m1	-2020m1
$h_i \times \mathrm{Post}_t$	0.003	0.134	0.187	-0.561	-0.485	-0.545
	[0.333]	[0.229]	[0.179]	[0.483]	[0.460]	[0.448]
$h_i \times KOR_j$	5.827***	5.949***	6.222***			
	[1.294]	[1.360]	[1.382]			
$KOR_j \times Post_t$	-0.705***	-0.678***	-0.633***			
	[0.070]	[0.048]	[0.049]			
$h_i \times \mathrm{KOR}_j \times \mathrm{Post}_t$	-1.176**	-1.294***	-1.565***			
	[0.485]	[0.332]	[0.235]			
Fixed effect						
Prefecture $(\psi_i)$	Yes	Yes	Yes	Yes	Yes	Yes
Country $(\psi_j)$	Yes	Yes	Yes	No	No	No
Time $(\psi_t)$	Yes	Yes	Yes	Yes	Yes	Yes
$\overline{N}$	52,879	17,573	12,037	2,726	893	611
$R^2$	0.840	0.850	0.850	0.970	0.970	0.970

Notes: Figures in brackets indicate standard errors clustered by prefecture, country, and time for columns (1)–(3) and by prefecture and time for columns (4)–(6). \*\*\* and \*\* indicate the significance level at 1 and 5 percent, respectively.

Source: Authors' estimation, based on Overnight Travel Statistics Survey.

Second, for the aggregate-level analysis, the coefficient of  $(h_i \times \text{Post}_t)$  is insignificant for all three sample periods. At first sight, this seems to suggest that the aggregate impact is common across regions. However, this does not necessarily contradict the diversification story. The difference in the results between the Herfindahl index  $h_i$  and the Korea dependency ratio  $s_i$  comes from the fact that some prefectures heavily depend upon exports to Korea while other prefectures depend upon exports to other countries. For example, suppose that some prefectures export only to Korea while other prefectures export only to China. Despite the fact that the export destinations are equally concentrated (i.e., less diversified) for both types of prefectures, the impact of the boycott appears only on the former prefectures, not the latter, if the boycott occurs only in Korea. Although the Herfindahl index is a useful measure of export diversification, a careful interpretation may be needed for the use of the Herfindahl index in analyzing the impact of a boycott, or that of a political conflict between two countries in general.

<sup>&</sup>lt;sup>57</sup>The DDD estimation results using prefecture-time, country-time and prefecture-country fixed effects are not shown in Table B2 due to space constraints. This specification produces coefficients of  $(h_i \times KOR_j \times Post_t)$  of -1.195, -1.308, and -1.597 for the full-, medium- and short-period samples, respectively, and all are significant at the 1 percent level. These values are very similar to those shown in Table B2, which supports the robustness of our results to the strictest possible specification.

<sup>&</sup>lt;sup>58</sup>Note that the correlation between  $h_i$  and  $s_i$  is 0.368, indicating that prefectures that are more export concentrated (i.e., less export diverse) also tend to be more Korea dependent, but the correlation is far from perfect.

## C Checking for Outlier Effects

### C.1 Excluding top 5 prefectures for receiving Korean visitors in 2018

Based on the skewed distribution of Korean visitors across Japanese provinces implied by Figure C1, one might ask whether outliers are driving our results. To test this hypothesis, we drop the top five prefectures in receiving Korean visitors in 2018 (i.e., Osaka, Tokyo, Fukuoka, Hokkaido and Okinawa) and repeat our disaggregate-level and aggregate-level analyses using our main specification. First we check the common trends assumption. Table C1 presents these results, with columns (1)–(3) showing the disaggregate-level results and columns (4)–(6) showing the aggregate-level results. The common trends assumption does not hold for either level of analysis for the short-period sample, but holds for the full- and medium-period samples. Therefore we report the regression results only for the full- and medium-period samples, similar to our reporting strategy in the main text.

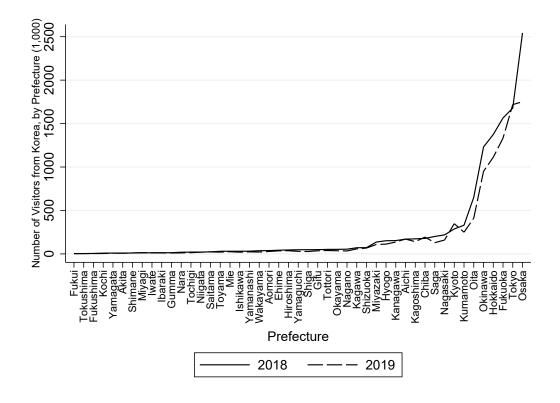


Figure C1: Number of Visitors from Korea in 2018 and 2019, by Prefecture

Notes: Total number of foreign visitors indicates the total number of visitors who reside outside of Japan times the number of nights stayed in Japan (unit: 1,000 person-nights).

Source: Japan Tourism Agency (2020) Overnight Travel Statistics Survey.

Table C2 reports our log linear estimation results, excluding the top five prefectures. Columns (1)–(2) correspond with the disaggregate analysis of equation (1) while columns (3)–(4) correspond with the aggregate analysis of equation (3). The size, sign and significance level of our variables of interest are similar to those reported earlier in Tables 3 and 7.

To more easily compare the regression results without the top five prefectures to our main results, we convert the estimated coefficients from Table  $C_2$  into growth rates in Tables  $C_3$  and  $C_4$  for the disaggregate-level and aggregate-level analyses, respectively. Note that the distribution of  $s_i$  changes slightly due to our exclusion of the top five prefectures. The average

Table C1: Common Trends Assumption: Excluding Top 5 Prefectures

	Disggregate-level analysis				Aggre	gate-level a	nalysis
	(1)	(2)	(3)	_	(4)	(5)	(6)
Period	2015m4	2018m7	2019m1		2015m4	2018m7	2019m1
	-2019m6	-2019m6	–2019m6		-2019m6	-2019m6	-2019m6
$s_i \times \mathrm{Trend}_t$	Yes	Yes	Yes		0.004	-0.04	-0.177**
					[0.007]	[0.027]	[0.069]
$s_i \times KOR_j \times Trend_t$	0.008	0.041	-0.441***				
	[0.007]	[0.025]	[0.017]				
Fixed effect							
Prefecture $(\psi_i)$	Yes	Yes	Yes		Yes	Yes	Yes
Country $(\psi_j)$	Yes	Yes	Yes		NA	NA	NA
Time $(\psi_t)$	Yes	Yes	Yes		Yes	Yes	Yes
$s_i \times KOR_j$	Yes	Yes	Yes		NA	NA	NA
$KOR_j \times Trend_t$	Yes	Yes	Yes		NA	NA	NA
$\overline{N}$	41,283	9,874	4,938		2,142	504	252
$R^2$	0.82	0.83	0.84		0.95	0.96	0.96

Notes: Figures in brackets indicate standard errors clustered by prefecture, country, and time for columns (1)–(3) and by prefecture and time for columns (4)–(6). \*\*\* and \*\* indicate the significance level at 1 and 5 percent, respectively.

Source: Authors' estimation, based on Overnight Travel Statistics Survey.

Table C2: Regression Results: Excluding Top 5 Prefectures

	Disggregate	e-level analysis	Aggregate-	level analysis
	(1)	(2)	(3)	(4)
Period	2015m4	2018m7	2015m4	2018m7
	-2020m1	-2020m1	-2020m1	-2020m1
$s_i \times \mathrm{Post}_t$	0.177	0.296**	-0.897***	-0.839***
	[0.135]	[0.129]	[0.181]	[0.137]
$s_i \times KOR_j$	8.052***	8.174***		
	[0.309]	[0.450]		
$KOR_j \times Post_t$	-0.530***	-0.508***		
	[0.034]	[0.024]		
$s_i \times KOR_j \times Post_t$	-2.372***	-2.490***		
	[0.122]	[0.127]		
Fixed effect				
Prefecture $(\psi_i)$	Yes	Yes	Yes	Yes
Country $(\psi_j)$	Yes	Yes	NA	NA
Time $(\psi_t)$	Yes	Yes	Yes	Yes
$\overline{N}$	47,082	15,673	2,436	798
$R^2$	0.82	0.82	0.95	0.96

Notes: Figures in brackets indicate standard errors clustered by prefecture, country, and time for columns (1)–(2) and by prefecture and time for columns (3)–(4). \*\*\* and \*\* indicate the significance level at 1 and 5 percent, respectively.

and the median of  $s_i$  are 14.1 percent and 9.9 percent, respectively, while the first and third quartiles are 5.0 percent and 15.4 percent, respectively. Using the longer two sample periods, which satisfied the common trends assumption, we see that prefectures with high (i.e., 75th percentile) dependency on visitors from Korea lost about 59.6 percent of their exports to Korea while prefectures with low (i.e., 25th percentile) Korea dependency lost about 47.9 percent. These estimates are within the 56.9 to 60.9 percent and 47.8 to 49.7 percent export loss ranges established in the main text.

The net effects on prefectural exports shown in Table C4 also are right in line with previous results. We find that prefectures with high Korea dependency lost about 12.5 percent of their total accommodations services exports while prefectures with low Korea dependency lost about 4.3 percent. These exports losses are within or only slightly above the ranges established in the main text (i.e., -10.5 to -13.3 percent and -3.3 to -4.2 percent, respectively). The export loss gap between the 75th percentile and 25th percentile prefecture for Korea dependency is -8.0 to -8.5 percentage points, which is as large as the export loss experienced by the median prefecture (i.e., -8.0 to -8.5), similar to our previous finding. This demonstrates that our main results are robust to the exclusion of the top five prefectures receiving visitors from Korea in 2018 (i.e., pre-boycott).

Table C3: Impact of the Boycott on Prefectures' Exports to Korea: Excluding Top 5 Prefectures

	(1)	(2)	(3)	(4)	(5)
	(-)	(-)	$(=(1)\times(2))$	(=(3) + KP Coeff.)	Total magnitude
Percentile	Coefficient	$s_i$	Relative magnitude	Total magnitude	converted
			(log change)	(log change)	(growth rate)
2015m4-202	0m1				
Mean	-2.372	0.141	-0.334	-0.864	-0.578
25%	-2.372	0.050	-0.118	-0.648	-0.477
50%	-2.372	0.099	-0.235	-0.765	-0.535
75%	-2.372	0.154	-0.366	-0.896	-0.592
75-25% gap					-0.115
2018m7-202	0m1				
Mean	-2.490	0.141	-0.350	-0.880	-0.585
25%	-2.490	0.050	-0.124	-0.654	-0.480
50%	-2.490	0.099	-0.246	-0.776	-0.540
75%	-2.490	0.154	-0.385	-0.915	-0.599
75-25% gap					-0.119

Notes: Exports to Korea mean the exports of accommodation services to Korea that are defined as the number of visitors from Korea (the total number of visitors who reside in Korea  $\times$  the number of nights stayed in Japan). Percentile indicates the quartiles of  $s_i$ . Coefficients are obtained from Table C2 and KP Coeff. means (KOR $_j \times \text{Post}_t$ ) coefficient from the corresponding sample period. Rounding off of displayed numbers explains small variations in calculated numbers shown above. Growth rate =  $\exp(\log \text{change}) - 1$ .

Source: Authors' estimation, based on Overnight Travel Statistics Survey.

#### C.2 Excluding top 4 prefectures for Korea dependency

As an additional robustness check, we also consider whether our results are driven by the disproportionate boycott effects on the prefectures that are most dependent on Korean visitors. As seen in Figure 4, Oita, Saga, and Yamaguchi prefectures all have very high Korea dependency and they suffered strong declines in visitors from Korea between 2018 and 2019. We check the robustness of our results by re-estimating the boycott effects after excluding these three prefec-

Table C4: Impact of the Boycott on Prefectures' Total Exports: Excluding Top 5 Prefectures

1	<i>J</i>		1	0 1
	(1)	(2)	(3)	(4)
			$(=(1) \times (2))$	Total magnitude
Percentile	Coefficient	$s_i$	Total magnitude	converted
			(log change)	(growth rate)
2015m4-2020	0m1			
Mean	-0.897	0.141	-0.126	-0.119
25%	-0.897	0.050	-0.045	-0.044
50%	-0.897	0.099	-0.089	-0.085
75%	-0.897	0.154	-0.138	-0.129
75-25% gap				-0.085
2018m7-2020	0m1			
Mean	-0.839	0.141	-0.118	-0.111
25%	-0.839	0.050	-0.042	-0.041
50%	-0.839	0.099	-0.083	-0.080
75%	-0.839	0.154	-0.129	-0.121
75-25% gap				-0.080

Notes: Exports mean the exports of accommodation services that are defined as the number of foreign visitors (the total number of visitors who reside outside of Japan  $\times$  the number of nights stayed in Japan). Percentile indicates the quartiles of  $s_i$ . Coefficients are obtained from Table C2. Rounding off of displayed numbers explains small variations in calculated numbers shown above. Growth rate =  $\exp(\log \operatorname{change}) - 1$ .

Source: Authors' estimation, based on Overnight Travel Statistics Survey.

tures, along with Fukuoka which reports a Korea dependency level close to Yamaguchi's level (i.e., 0.4399 versus 0.4548, as shown in Table 5).

The regression results for both the disaggregate and aggregate levels after excluding the top four prefectures for Korea dependency are shown in Table C5. We report results for the full- and medium-period samples for comparative purposes with the results reported in the main text. The size, sign and significance level of our variables of interest are similar to those reported earlier in Tables 3 and 7.

To facilitate a comparison of the results without the top four prefectures for Korea dependency with our main results, we convert the estimated coefficients in Table C5 into growth rates in Tables C6 and C7 for the disaggregate-level and aggregate-level analyses, respectively. Again, note that the distribution of  $s_i$  changes slightly due to our exclusion of the top four prefectures for Korea dependency. The average of  $s_i$  declines to 11.8 percent, while the first, second and third quartiles drop to 5.0, 9.7 and 15.4 percent, respectively.

Across the longer two sample periods, we estimate that prefectures with low (i.e., 25th percentile) Korea dependency lost about 46.6 percent of their exports to Korea, as shown in Table C6. This estimated loss is only slightly below the 47.8 to 49.7 percent export loss range reported in the main text. Prefectures with high (i.e., 75th percentile) Korea dependency lost about 61.0 percent of their exports to Korea, which is slightly above the 56.9 to 60.9 percent range established in the main text. Similarly, the net effects on prefectural exports reported in Table C7 are within or only slightly below the ranges reported in the main text and shown in Table 9. For example, after dropping the top four prefectures for Korea dependency, we estimate an about 9.7 percent loss in total exports for high (i.e., 75th percentile) Korea dependency prefectures, which is slightly below the 10.5 to 13.3 percent range established in the main text. Dropping the top four prefectures for Korea dependency changes our point estimates marginally, but not in a substantive way. We conclude that our main message is robust to excluding these outlier prefectures for Korea dependency.

Table C5: Regression Results: Excluding Top 4 Prefectures for Korea Dependency

	Disggregate	e-level analysis	Aggregate-	level analysis
	(1)	(2)	(3)	(4)
Period	2015m4	2018m7	2015m4	2018m7
	-2020m1	-2020m1	-2020m1	-2020m1
$s_i \times \mathrm{Post}_t$	0.587**	0.642***	-0.671**	-0.645***
	[0.227]	[0.134]	[0.301]	[0.182]
$s_i \times \mathrm{KOR}_j$	10.131***	10.372***		
	[0.564]	[0.653]		
$KOR_j \times Post_t$	-0.496***	-0.459***		
	[0.021]	[0.027]		
$s_i \times \mathrm{KOR}_j \times \mathrm{Post}_t$	-2.883***	-3.126***		
	[0.333]	[0.279]		
Fixed effect				
Prefecture $(\psi_i)$	Yes	Yes	Yes	Yes
Country $(\psi_j)$	Yes	Yes	NA	NA
Time $(\psi_t)$	Yes	Yes	Yes	Yes
$\overline{N}$	48,427	16,094	2,494	817
$R^2$	0.85	0.85	0.97	0.97

Notes: Figures in brackets indicate standard errors clustered by prefecture, country, and time for columns (1)–(2) and by prefecture and time for columns (3)–(4). \*\*\* and \*\* indicate the significance level at 1 and 5 percent, respectively.

Source: Authors' estimation, based on Overnight Travel Statistics Survey.

Table C6: Impact of the Boycott on Prefectures' Exports to Korea: Excluding Top 4 Prefectures for Korea Dependency

	(1)	(2)	(3)	(4)	(5)
			$(=(1)\times(2))$	(=(3) + KP Coeff.)	Total magnitude
Percentile	Coefficient	$s_i$	Relative magnitude	Total magnitude	converted
			(log change)	(log change)	(growth rate)
2015m4-202	0m1				
Mean	-2.883	0.118	-0.340	-0.836	-0.566
25%	-2.883	0.050	-0.143	-0.639	-0.472
50%	-2.883	0.097	-0.279	-0.775	-0.539
75%	-2.883	0.154	-0.445	-0.941	<b>-</b> 0.610
75-25% gap					-0.137
2018m7-202	0m1				
Mean	-3.126	0.118	-0.368	-0.827	-0.563
25%	-3.126	0.050	-0.156	-0.615	-0.459
50%	-3.126	0.097	-0.302	-0.761	-0.533
75%	-3.126	0.154	-0.483	-0.942	-0.610
75-25% gap					-0.151

Notes: Exports to Korea mean the exports of accommodation services to Korea that are defined as the number of visitors from Korea (the total number of visitors who reside in Korea  $\times$  the number of nights stayed in Japan). Percentile indicates the quartiles of  $s_i$ . Coefficients are obtained from Table C5 and KP Coeff. means (KOR $_j \times \text{Post}_t$ ) coefficient from the corresponding sample period. Rounding off of displayed numbers explains small variations in calculated numbers shown above. Growth rate = exp(log change) -1.

Table C7: Impact of the Boycott on Prefectures' Total Exports: Excluding Top 4 Prefectures for Korea Dependency

	(1)	(2)	(3)	(4)
			$(=(1)\times(2))$	Total magnitude
Percentile	Coefficient	$s_i$	Total magnitude	converted
			(log change)	(growth rate)
2015m4-2020	0m1			
Mean	-0.671	0.118	-0.079	-0.076
25%	-0.671	0.050	-0.033	-0.033
50%	-0.671	0.097	-0.065	-0.063
75%	-0.671	0.154	-0.104	-0.098
75-25% gap				-0.066
2018m7-2020	0m1			
Mean	-0.645	0.118	-0.076	-0.073
25%	-0.645	0.050	-0.032	-0.032
50%	-0.645	0.097	-0.062	-0.060
75%	-0.645	0.154	-0.100	-0.095
75-25% gap				-0.063

Notes: Exports mean the exports of accommodation services that are defined as the number of foreign visitors (the total number of visitors who reside outside of Japan  $\times$  the number of nights stayed in Japan). Percentile indicates the quartiles of  $s_i$ . Coefficients are obtained from Table C5. Rounding off of displayed numbers explains small variations in calculated numbers shown above. Growth rate = exp(log change) -1.

# D Common Trends Assumption for Overall Trade of Accommodation Services

To evaluate the common trends assumption for Japan's overall exports of accommodation services in equation (7), we run the following regression:

$$Y_{it} = \alpha + \psi_i + \psi_t + \tau(KOR_i \times Trend_t) + \varepsilon_{it}.$$
 (D1)

As in equation (2), Trend<sub>t</sub> cannot be included by itself due to the collinearity with  $\psi_t$ . The numbers of observations for the test of the common trends assumption thus are 1,020 (= 20 origin countries × 51 months), 240 (= 20 origin countries × 12 months), and 120 (= 20 origin countries × 6 months) for the full-, medium-, and short-period samples, respectively. If the trend is common between Korea and other countries,  $\tau$  will be insignificant.

Columns (1)–(3) in Table D1 present the regression results for equation (D1). The results indicate significant coefficients for the full-, medium-, and short-period samples. The results suggest that the common trends assumption does not hold for this analysis, which makes it difficult for us to apply the DID design to regression equation (7).

Table D1: Common Trends Assumption: Alternative Aggregation

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	(1)	(2)	(3)	(4)		
Period	2015m4	2018m7	2019m1	2015m4		
	-2019m6	-2019m6	-2019m6	-2019m6		
$\overline{\mathrm{KOR}_{j} \times \mathrm{Trend}_{t}}$	0.005***	-0.025***	-0.157***	0.004***		
•	[0.001]	[0.007]	[0.027]	[0.001]		
Fixed effect						
Country $(\psi_j)$	Yes	Yes	Yes	No		
Time $(\psi_t)$	Yes	Yes	Yes	Yes		
Country-month ( $\psi_{jm}$ )	No	No	No	Yes		
$\overline{N}$	1,020	240	120	1,020		
$R^2$	0.94	0.94	0.96	0.99		

Notes: Figures in brackets indicate standard errors clustered by country and time. \*\*\* indicates the significance level at 1 percent.

Source: Authors' estimation, based on Overnight Travel Statistics Survey.

One may be concerned that the number of foreign visitors is not only affected by country-specific factors but also affected by country-specific seasonality as we confirmed in Figure 1. To address this concern, we include country-month-fixed effects  $\psi_{jm}$ , instead of country-fixed effect  $\psi_j$  for the full-period sample.<sup>59</sup> Column (4) presents the results, indicating significant coefficients. Once again, the results do not support the common trends assumption even if we control for unobserved country-month specific effects.<sup>60</sup> These results together suggest that the common trends assumption does not hold for the Japanese accommodations data for total exports to Korea relative to other countries. Applying the DID design to equation (7) thus is not appropriate with our dataset.

We also examined whether the common trends assumption holds for equation (8) using the Korean data for the full sample (i.e., 2015m4–2019m6). As shown in Table D2, we found that the common trends assumption did not hold for Korean outbound and inbound data.

<sup>&</sup>lt;sup>59</sup>It is impossible to include country-month-fixed effect for the middle- and short-period samples because they cover only 12 and 6 months, respectively.

 $<sup>^{60}</sup>$ To control for seasonality, one can also compute the dependent variable as the ratio or difference from the same month in the previous year (e.g.,  $Y_{jt}/Y_{j,t-12}$ ). However, such analysis leads to comparisons of growth rates or changes, rather than levels.

Therefore, we present the results using the Korean data just as a reference, not as a main result.

Table D2: Common Trends Assumption: Korean data

	(1)	(2)	
	Outbound	Inbound	
Period	2015m4	2015m4	
	-2019m6	-2019m6	
$\overline{\mathrm{KOR}_j \times \mathrm{Trend}_t}$	0.010***	0.012***	
	[0.001]	[0.001]	
Fixed effect			
Country $(\psi_j)$	Yes	Yes	
Time $(\psi_t)$	Yes	Yes	
$\overline{N}$	1,477	9,870	
$R^2$	0.97	0.97	

Notes: Figures in brackets indicate standard errors clustered by country and time. \*\*\* indicates the significance level at 1 percent.

Source: Authors' estimation, based on data from the Korea Tourism Organization website.