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Tsutomu Watanabe
Graduate School of Economics, University of Tokyo

Yuki Omori
Nowcast Inc.

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# Online Consumption During and After the COVID-19 Pandemic: Evidence from Japan

Tsutomu Watanabe* Yuki Omori†

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**Abstract**

The spread of COVID-19 infections has led to substantial changes in consumption patterns. While demand for services that involve face-to-face contact has decreased sharply, online consumption of goods and services, such as through e-commerce, is increasing. The aim of this paper is to investigate whether online consumption will continue to increase even after COVID-19 subsides. Online consumption requires upfront costs, which have been regarded as one of the factors inhibiting the diffusion of online consumption. However, if many consumers made such upfront investments due to the pandemic, they would have no reason to return to offline consumption after the pandemic has ended. We examine whether this was actually the case using credit card transaction data. Our main findings are as follows. First, the main group responsible for the increase in online consumption are consumers who were already familiar with it before the pandemic. These consumers increased the share of online spending in their overall spending. Second, some consumers that had never used the internet for purchases before started to do so due to COVID-19. However, the fraction of consumers making this switch was not very different from the trend before the crisis. Third, by age group, the switch to online consumption was more pronounced among youngsters than seniors. These findings suggest that it is not the case that during the pandemic a large number of consumers made the upfront investment necessary to switch to online consumption, so a certain portion of the increase in online consumption is likely to fall away again once COVID-19 subsides.

*Graduate School of Economics, University of Tokyo. E-mail: watanabe@e.u-tokyo.ac.jp. Website: https://sites.google.com/site/twatanabelab/ We would like to thank Yasutora Watanabe, David Weinstein, and Tomoyoshi Yabu for helpful discussions. This research forms part of the project on "Central Bank Communication Design" funded by the JSPS Grant-in-Aid for Scientific Research No. 18H05217. This paper is an updated version of "Online Consumption During and After the COVID-19 Pandemic: Evidence from Japan," In E. Mazaheri (Ed.), *The Impact of COVID-19 On E-Commerce*, Proud Pen, Published: 20 May 2021.

†Nowcast Inc. Email: omori@nowcast.co.jp.

# 1 Introduction

People's consumption patterns have changed substantially as a result of the spread of the COVID-19 infections. One such change is a reduction in the consumption of services that involve face-to-face contact. For instance, "JCB Consumption NOW" data, credit card transaction data provided jointly by JCB Co., Ltd., and Nowcast Inc., show that, since February this year, spending on eating out, entertainment, travel, and lodging have shown substantial decreases. Even in the case of goods consumption, there has been a tendency to avoid face-to-face contact such as at convenience stores and supermarkets. For example, with regard to supermarket shopping, the amount of spending per consumer has increased, but the number of shoppers has decreased, indicating that consumers purchase more than usual at supermarkets but try to minimize the risk of infection by reducing the number of visits. Another important change is the increase in the consumption of services and goods that do not involve face-to-face contact. The credit card transaction data indicate that with regard to services consumption, spending on movies and theaters has decreased substantially, while spending on streaming media services has increased. As for the consumption of goods, so-called e-commerce, i.e., purchases via the internet, has shown substantial increases.

It is not surprising that consumers concerned about their health shifted their demand from face-to-face to non-face-to-face consumption activities amid the coronavirus pandemic.[1] This trend was also spurred by stay-at-home requests from the national and local governments. The question we aim to address in this paper is what will happen after COVID-19 subsides. Will demand shift back?

There are many who think that the world after the pandemic will be different from before. With regard to personal consumption, too, it has been argued that once demand patterns have

[1]Using data from an agri-food e-commerce platform in Taiwan to investigate how the pandemic affects the demand for online food shopping services in Taiwan, Chang and Meyerhoefer (2020) show that an additional confirmed case of COVID-19 increased sales by 5.7% and the number of customers by 4.9%. Meanwhile, based on a survey in China, Gao et al. (2020) show that a larger number of confirmed cases increases the likelihood that consumers purchase food online, especially among young people that regard online purchases as associated with little risk and that live in large cities.

shifted, they will not change back.[2] For example, the number of cinemas and theaters has been declining since before the pandemic, reflecting a shift toward the consumption of streaming media services. The pandemic has simply accelerated this trend, and it is possible that the pandemic may serve as the death knell for such services, making the demand shift irreversible. In this paper, among these shifts in demand associated with the pandemic, we focus on online consumption and consider whether the demand shifts are irreversible.

Online consumption is more convenient than over-the-counter purchases in a number of respects.[3] The first is a reduction in transportation costs in the sense that one does not have to physically go to the store. Transportation cost savings also include cost savings in the sense that one does not have to carry what one bought. The second is the reduction in search costs. The internet is full of different products and services, and the variety of products and services offered is more diverse than that offered at physical stores. There is also a large variety of prices. The internet makes it easy to compare the quality and prices of products one wants to buy. While for the period before the coronavirus pandemic, studies by Dolfen et al. (2019) and Jo et al. (2019) examining the increase in consumer utility (consumer surplus) through the advantages of online consumption such as the reduction in transportation costs and the increase in product variety find that the gain in consumer surplus is equivalent to 1% of personal consumption.[4]

However, if online consumption is so attractive, all consumers should have switched to online consumption regardless of the pandemic; yet, this is not the case. In addition, the degree of

[2] See, for example, the following articles:
`https://www.bloombergquint.com/business/outbreak-pushes-japan-s-shoppers-to-finally-buy-things-online`
`https://www.japantimes.co.jp/news/2020/05/09/business/economy-business/retail-reinvention-coronavirus/#.Xsc38mj7R1w`
UNCTAD (2020) conducted a survey in nine countries to examine how the pandemic has changed the ways consumers use e-commerce, showing that many of the respondents shop online more frequently than before, and that more than half of the respondents anticipate to continue shopping online more than before in the post-COVID era. WTO (2020) notes that the SARS epidemic in China in 2002-03 spurred the growth of firms such as Taobao, a Chinese online shopping website, and points out that COVID-19 may also bring about a sustained expansion in online consumption. See Clark (2018) for an interesting account of the take off of Taobao in the wake of SARS.

[3] For more details on this point, see, for example, Goldfarb and Tucker (2019a, b), Huang and Bronnenberg (2020), and Gupta et al. (2004).

[4] Using data for Japan, Jo et al. (2019) examine the increase in the consumer surplus resulting from e-commerce. Meanwhile, using Visa card data from the United States, Dolfen et al. (2019) measure travel cost savings and the gains from product variety.

adoption of online consumption varies widely across countries and regions and is relatively low in Japan compared to the United States, Europe, China, and South Korea.[5]

Factors that inhibit the spread of online consumption are, firstly, the fixed costs involved in switching to online consumption.[6] Online shopping, needless to say, requires a smartphone or PC as well as internet access. Costs are not limited to these physical upfront investments. It is necessary to learn how to operate, e.g., a smartphone and how to browse websites and make purchases. Given the need for hard upfront investment as well as soft investment in the form of learning, consumers decide whether to move to online consumption based on a comparison of those upfront investment costs and the benefits of online consumption. The second reason potentially inhibiting the switch to online consumption is privacy concerns, i.e., concerns about handing over information on purchases to stores and firms. For sellers, online purchases by consumers have the advantage that they significantly reduce the cost of tracking buyers. Moreover, they provide sellers with effective means for advertising and price discrimination. Buyers, on the other hand, may be concerned that online purchases may result in the leak of personal information. Consumers with these concerns are strongly reluctant to make online purchases. Third, online consumption gives rise to information asymmetry, where buyers cannot directly check the quality of goods and services. This problem is particularly serious when the quality of products such as fresh food varies widely, or when there is no relationship of trust between the buyer and the seller.

The spread of coronavirus infections drastically increased the attractiveness of online consumption by allowing consumers to avoid face-to-face contact when making purchases and led many consumers to go online. However, once the coronavirus pandemic subsides, this attraction will fade. Will consumers then go back to offline shopping? There are two possible reasons why they might not return, that is, why the shift to online shopping could be irreversible. The first is the upfront costs of moving online. If consumers that had never shopped online have

[5]For the development of e-commerce markets in Japan, see, for example, "E-commerce Market Survey" conducted by the Ministry of Economy, Trade and Industry, which is available at `https://www.meti.go.jp/english/press/2020/0722_005.html`.

[6]See, for example, Cai and Cude (2016).

paid the upfront costs and started shopping online, there is no reason for them to go back to offline shopping. Since they paid the upfront costs, they will probably continue to shop online to recoup these costs. The second reason is that the concerns that consumers may have had about online shopping such as the leakage of personal information and information asymmetry likely will have been dispelled during the actual experience of online shopping. If this experience changes the perceptions of online shopping that consumers had before the pandemic, they will continue to shop online after the virus subsides.

What should be highlighted is that both of the above two reasons apply only to consumers that did not use the internet for online purchases before the pandemic and only started doing so during the pandemic. In contrast, consumers that were already used to making online purchases before the pandemic did not need to make any upfront investment or adjust their perceptions, so that even if they increased their online consumption during the pandemic, their online consumption will likely return to the level before the pandemic once the risk of infection subsides.

Thus, in order to know whether the increase in online consumption demand due to the pandemic is irreversible, it is necessary to decompose the increase in online consumption into (1) the contribution due to the entry of new consumers that had never used the internet for purchases before, and (2) the contribution due to the increase in the share of online purchases of those that already shopped online before, and to examine whether the former dominates the latter.

The rest of this paper is organized as follows. Section 2 introduces the data used in this paper and then explains our empirical methodology. The analysis in this paper will focus on a sample of 1 million consumers from the "JCB Consumption NOW" data. To start with, using data for before the outbreak of the pandemic (January 2020), we classify consumers into whether they made online purchases. Then, using data for April 2020, we examine whether, during the pandemic, (1) consumers that had never made online purchases started to do so, and (2) whether consumers that were already making online purchases before increased the share of their purchases they did online. Section 3 then presents the estimation results, while Section 4 uses the estimation results to forecast how online consumption will change in the future. Section 5 concludes.

# 2 Data and Empirical Methodology

## 2.1 Data

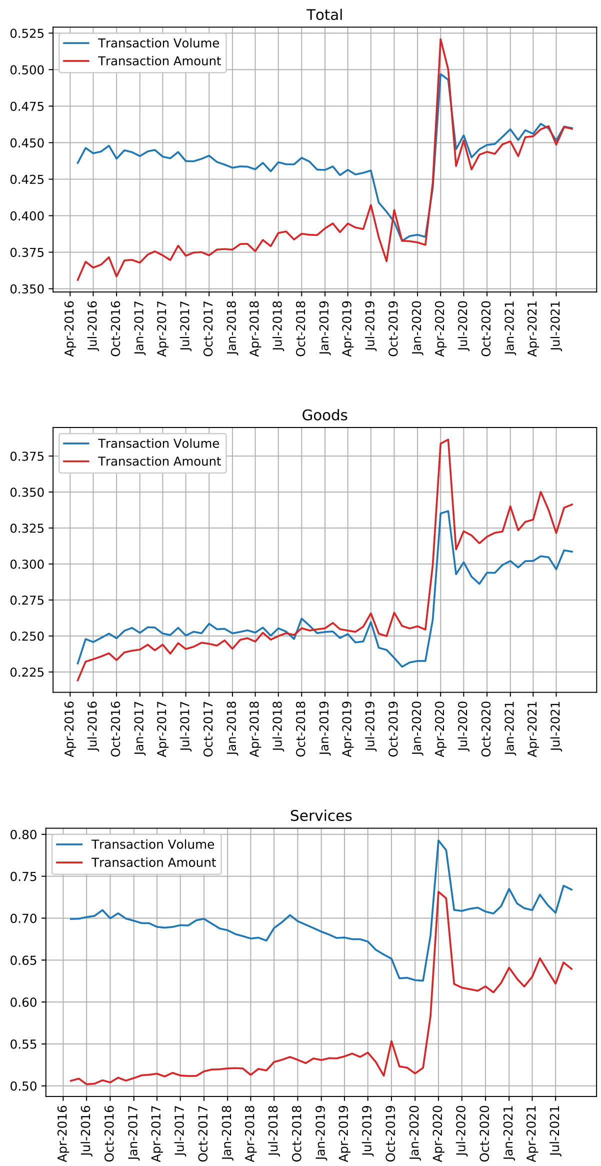
The "JCB Consumption NOW" data are collected from 1 million active JCB members that are randomly sampled from the entire card members.[7] The data have been processed according to the procedure adopted by JCB Co., Ltd. to make it impossible to identify individuals. The data used in this paper consist of individual transaction records for these 1 million consumers in January, April, July, and October 2020, and the corresponding four months a year earlier. JCB classifies individual transactions into online and offline transactions depending on whether the payments associated with them were implemented online or in person. We follow this when we classify individual transactions of a consumer in a particular month into online purchases and offline purchases. By doing this for the month before the outbreak of the pandemic, we can define for each consumer whether or not they were already making purchases online. Similarly, by doing this for the months following the outbreak of the pandemic, we can see if consumers that had not made purchases online before started to do so during the pandemic.

## 2.2 Outbreak of COVID-19 and the Surge in Online Consumption

Figure 1 shows the share of online transactions in overall credit card transactions. The online share is calculated in terms of the transaction volume (i.e., the number of transactions), which is shown by the blue line, as well as in terms of the transaction amount, which is shown by the red line. The upper, middle, and lower panels are for overall expenditures, for expenditures on goods, and for expenditures on services, respectively. The upper panel shows that there was an upward trend in the online share in terms of the transaction amount before the COVID-19

[7] See `https://www.jcbconsumptionnow.com/en` for more details on "JCB Consumption Now." Other studies using credit card transaction data to examine switching between offline and online consumption during the pandemic include Yilmazkuday (2020) for the United States and Bounie et al. (2020) for France.

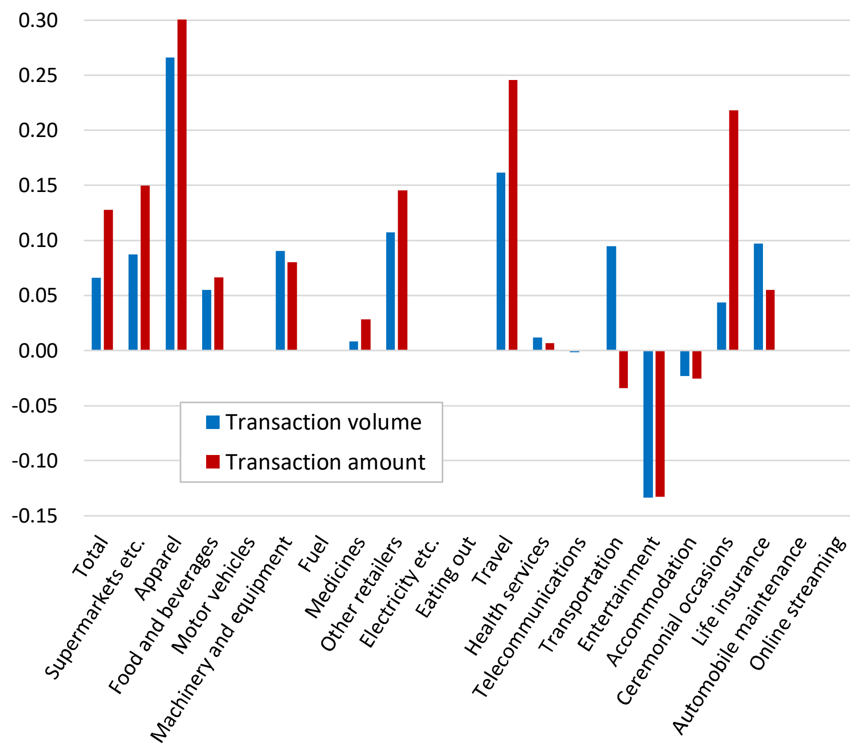
## Figure 1 Share of Online Consumption




**Note**: The blue and red lines show the share of online consumption in terms of the transaction volume (i.e., the number of transactions) and in terms of the transaction amount, respectively. Seasonally adjusted.

crisis, and that the online share in January 2020, just before the outbreak of the pandemic in Japan, was 39%. On the other hand, the online share in terms of the transaction volume

**Figure 2 Changes in Online Share by Expenditure Category**




**Note**: The blue and red bars show changes in the share of online consumption in individual expenditure categories between April 2019 and April 2020. The blue and red bars represent the share of online consumption in terms of the transaction volume (i.e., the number of transactions) and in terms of the transaction amount, respectively.

showed a weak downward trend before the crisis and was 38% in January 2020.

The number of new infections in Japan started to increase rapidly in late March, and the government responded by closing schools on February 27 and declaring a state of emergency on April 16.[8] In response to the spread of infections, people quickly switched to online consumption

[8]The first reported case of a COVID-19 infection in Japan – of a man who had traveled to Wuhan, China – was on January 16, 2020. Then, on February 5, 10 passengers of a cruise ship docked at Yokohama Port were confirmed to have caught the virus. The first death in Japan was reported on 10 February. In response to the spread of infections, the government on February 27 requested elementary, junior high, and high schools nationwide to temporarily close, and on March 24 decided to postpone the Tokyo Olympic Games scheduled for the summer of 2020. Furthermore, on April 7, a state of emergency was declared for seven prefectures including Tokyo, and on April 16, this was expanded to all prefectures. See Watanabe and Yabu (2020) for more details

in order to reduce face to face contact with others when shopping, so that the online share in terms of the transaction amount jumped up to 42% in March and 52% in April. Similarly, the online share in terms of the transaction volume increased to 42% in March and 50% in April. However, as the number of new infections started to decline in late April, the online shares dropped to 43% in terms of the transaction amount and 45% in terms of the transaction volume. The online shares have been stable at around 45% since then. Looking at the online shares for goods and services consumption separately shows that they are quite similar in that they registered a jump in March and April, declined again in May, and have been relatively unchanged since then at a generally elevated level when compared to the pre-COVID period.

Figure 2 shows the change in online shares from April 2019 to April 2020 by expenditure category. Expenditures on goods such as apparel and machinery and equipment showed a substantial increase in online shares. Turning to service categories, expenditure on travel and on ceremonial occasions showed increases of more than 20 percentage points in their online shares. On the other hand, the online share for entertainment expenditure declined more than 10 percentage points.

The online share for expenditure overall can be calculated by taking the average of the online shares in the individual expenditure categories. Specifically, it can be expressed as $\sum_{it} \omega_{it}\theta_{it}$, where $\theta_{it}$ is the online share for category $i$ in period $t$, and $\omega_{it}$ is the expenditure share of category $i$ in expenditure overall. The change in the online share for expenditure overall from April 2019 to April 2020 can then be decomposed as follows: $\sum_i \omega_{i,\text{Apr 2019}}(\theta_{i,\text{Apr 2020}} - \theta_{i,\text{Apr 2019}}) + \sum_i \theta_{i,\text{Apr 2019}}(\omega_{i,\text{Apr 2020}} - \omega_{i,\text{Apr 2019}})$. This indicates that an increase in the online share for expenditure overall occurs through two channels: (1) a switch in expenditure from offline to online within an expenditure category, which is represented by the first term; and (2) a switch in expenditure from a category with a low online share to a category with a high online share, which is represented by the second term. Calculation based on the transaction amount indicates that of the rise in the online share from April 2019 to April 2020 of 12.6 percentage points, 7.2

on the spread of infections and the government response.

percentage points are accounted for by the switch *within* categories and 5.4 percentage points are accounted for by the switch *across* categories. Similarly, calculation based on the transaction volume indicates that of the rise in the online share of 6.3 percentage points, 4.8 percentage points are due to the switch *within* categories and 1.5 percentage points are due to the switch *across* categories. These results suggest that, during the COVID-19 crisis, consumers not only switched from offline to online spending within categories but also from categories with a low online share, such as entertainment, to other categories with a high online share, such as online streaming.

### 2.3 Consumers' switch between online and offline shopping

For a particular month, consumers can be categorized into three types: (1) those who make offline purchases only (labelled "Offline only"), (2) those who make both online and offline purchases (labelled "Both"), and (3) those who make online purchases only (labelled "Online only"). Taking April 2019 and April 2020 as an example, let us consider a person who fell into the "Offline only" category in April 2019 and switched to "Both" in April 2020. In other words, this consumer shopped offline only in April 2019 (before the pandemic) but started making online purchases due to the pandemic.[9] There are three statuses, i.e., "Offline only," "Both," and "Online only", both in April 2019 and in April 2020, so that there are 9 possible transition patterns from April 2019 to April 2020.

### 2.4 Transition probabilities

In order to examine the transition from April 2019 to April 2020, we define the following conditional probability:

$$\Pr(\text{“Both” in April 2020} \,|\, \text{“Offline only” in April 2019}) \tag{1}$$

[9] However, it should be noted that even if a person is classified as "Offline only" in April 2019, we cannot say for certain that the person never made any online purchases before. It could be that the consumer happened to not make any online purchases in April 2019 despite having done so before. Being able to go back in time and look at this consumer's transaction history would provide us with a more accurate picture of the person's online purchasing behavior. However, "JCB Consumption NOW" does not allow tracing the consumption of a particular individual back in time in order to protect personal information by making it impossible to identify individuals.

This indicates how many of the consumers classified as "Offline only" in April 2019 transitioned to "Both" in April 2020. Similarly, the probabilities of the nine different transition patterns are defined as follows:

$$a_{ij} \equiv \Pr(\text{Status}\, i \text{ in April 2020}\, | \text{Status}\, j \text{ in April 2019}) \tag{2}$$

where status $i$ and $j$ represent the three types of consumers, i.e., "Offline only," "Both," and "Online only."

We denote the transition probability matrix consisting of elements $a_{ij}$ defined in equation (2) by $A$. $A$ is the transition probability matrix comparing April of this year with April of the previous year. Similarly, we define $B$ as the transition probability matrix comparing January of this year with January of the previous year. Part (a) of Table 1 presents the transition probabilities from January 2019 to January 2020, i.e., matrix $B$ calculated using actual data. The results for $A$, the transition probabilities from April 2019 to April 2020 are shown in part (c) of the table.

Matrix $B$ in the table indicates that while the share of the consumers who fell into the "Offline only" category in January 2019 and transitioned to "Both" in January 2020 was 14.6%, the transition probability from "Both" to "Offline only" was 4.0%, which shows that there was a trend toward online consumption before the pandemic. Similarly, the transition probability from "Offline only" to "Online only" was 3.9%, while the transition probability in the opposite direction was 1.4%. On the other hand, looking at the transition from "Both" to "Online only" shows that the probability was 14.4%, while the transition probability in the opposite direction was 17.4%, suggesting that the trend toward online consumption was receding relative to a year earlier.

Next, looking at matrix $A$, the transition probability from "Offline only" to "Both" was 18.0%, suggesting that the trend to online consumption has increased since January 2020. Similarly, the transition probabilities from "Offline only" to "Online only" and from "Both" to "Online only" are both higher than before the outbreak of the pandemic (i.e., in January 2020). This suggests that many of those that used to shop offline only started to shop online

**Table 1 Transition probabilities for online consumption**

| | | | | |
|---|---|---|---|---|
| (a) Transition from Jan 2019 to Jan 2020 | | | | |
| | | Jan 2019 | | |
| | | Offline only | Both | Online only |
| Jan 2020 | Offline only | 0.8154 | 0.0395 | 0.0139 |
| | Both | 0.1458 | 0.8164 | 0.1744 |
| | Online only | 0.0388 | 0.1441 | 0.8117 |
| (b) Transition from Jan 2019 to Jan 2020: Quarterly basis | | | | |
| | | Jan 2019 | | |
| | | Offline only | Both | Online only |
| Jan 2020 | Offline only | 0.9494 | 0.0113 | 0.0031 |
| | Both | 0.0419 | 0.9463 | 0.0511 |
| | Online only | 0.0085 | 0.0422 | 0.9457 |
| (c) Transition from Apr 2019 to Apr 2020 | | | | |
| | | Apr 2019 | | |
| | | Offline only | Both | Online only |
| Apr 2020 | Offline only | 0.7425 | 0.0495 | 0.0174 |
| | Both | 0.1800 | 0.7331 | 0.1477 |
| | Online only | 0.0775 | 0.2174 | 0.8349 |
| (d) Transition from Jan 2020 to Apr 2020: Based on Assumption A | | | | |
| | | Jan 2020 | | |
| | | Offline only | Both | Online only |
| Apr 2020 | Offline only | 0.9076 | 0.0162 | 0.0023 |
| | Both | 0.0608 | 0.8971 | -0.0118 |
| | Online only | 0.0315 | 0.0866 | 1.0094 |
| (e) Transition from Jan 2020 to Apr 2020: Based on Assumption B | | | | |
| | | Jan 2020 | | |
| | | Offline only | Both | Online only |
| Apr 2020 | Offline only | 0.8624 | 0.0258 | 0.0059 |
| | Both | 0.0953 | 0.8492 | 0.0348 |
| | Online only | 0.0422 | 0.1249 | 0.9591 |

**Notes**: "Online only" refers to those who make online purchases only, "Both" to those who make both online and offline purchases, and "Offline only" to those who make offline purchases only. Panel (b) shows the results in panel (a) converted to a quarterly basis by raising them to the power of 1/4.

due to the pandemic and many of those that used to shop both online and offline switched to online shopping only due to the pandemic.

### 2.5 Transition probabilities from January 2020 to April 2020

Both $A$ and $B$ provide comparisons with the same month of the previous year, so that seasonal factors are eliminated. Moreover, because the impact of the point reward system introduced by the government in October 2019 is included in both $A$ and $B$,[10] comparing $A$ and $B$ is also convenient in that it makes it possible to exclude the impact of the point reward system. By comparing April 2020 in the midst of the pandemic with January 2020, the month immediately preceding the pandemic, it is possible to extract the impact of the pandemic only. Unfortunately, the transition probability matrix between January 2020 and April 2020 is not available in the data due to data restrictions.[11] However, it can be estimated from $A$ and $B$ as shown below.

Denoting the transition probability matrix from January 2020 to April 2020 by $X$, the following relationship holds:

$$XB = AY \tag{3}$$

where $Y$ is a matrix that represents the transition probabilities from January 2019 to April 2019. $B$ on the left-hand side of equation (3) connects January 2019 and January 2020, and $X$ connects January 2020 and April 2020, so that $XB$ links the status in January 2019 with the status in April 2020. Similarly, $AY$ links the status in January 2019 with the status in April

[10] The point reward system was introduced in October 2019 as part of the Ministry of Economy, Trade and Industry's Point Reward Project, which provides subsidies for small and medium-sized enterprises and micro enterprises that wish to issue point rewards for consumers using cashless payment. The aim of the project was to prevent a drop in consumption after the consumption tax hike in April 2019, to improve the productivity of eligible businesses, and to increase convenience for consumers through the further dissemination of cashless payments. For example, consumers making a purchase using a cashless payment method such as a credit card will receive 2% or 5% of the purchase price back in points or cash. See `https://www.meti.go.jp/english/press/2019/0312_001.html` for more details on this program.

[11] In our dataset, transaction records for January 2020 and a year earlier, January 2019, are available for a random sample of card members taken in January 2020. Similarly, transaction records for April 2020 and a year earlier, April 2019, are available for a different random sample of card members taken in April 2020. To protect personal information, the data provided by JCB Co. Ltd. make it impossible to identify individuals, so that we cannot link the January and April samples to examine how individual consumers changed their purchasing behavior.

2020. Equation (3) yields

$$X = AYB^{-1} \tag{4}$$

Since $A$ and $B$ can be calculated from the data, $X$ can be estimated if $Y$ is known.

For $Y$, we make the following two simplifying assumptions and then estimate $X$ under each assumption. The first assumption is

$$Y = I \tag{5}$$

where $I$ is a $3 \times 3$ identity matrix. It is assumed that between January 2019 and April 2020 there were no significant shocks that may have affected the trend toward online consumption so that consumers' status remained unchanged. In the following, equation (5) will be referred to as Assumption $A$.

However, it is likely that the trend toward online consumption would have continued to advance steadily even without major shocks such as the introduction of the point reward system or the pandemic. We assume that the underlying trend toward online consumption can be captured by the transitions from January 2019 to January 2020, so that

$$Y = B^{3/12} \tag{6}$$

Note that we raise $B$ to the power of 3/12 to adjust for the difference in the length of the periods, i.e., 3 months (from January to April) and 12 months (from January to January of the following year). We refer to this as Assumption $B$.

Substituting (5) into (4) yields

$$X = AB^{-1} \tag{7}$$

and (6) into (4) yields

$$X = AB^{-3/4}. \tag{8}$$

Panels (d) and (e) of Table 1 show the results of calculating the transition probabilities from January 2020 to April 2020 using equations (7) and (8). Comparing the two shows that the individual elements of the matrices do not exactly match, and for some matrix elements there are non-negligible differences. However, the relative sizes qualitatively are almost identical, suggesting that equations (7) and (8) provide reliable estimates of $X$.

### 2.6 Online consumption shares

So far, we have explained how we examine the transitions between the three statuses of "Offline only," "Online only," and "Both." However, among those falling into the "Both" category, there will be some that make almost no offline purchases and are extremely close to falling into the "Online only" category and, conversely, some that make hardly any online purchases and are close to falling into the "Offline only" category. The following describes in more detail our approach for analyzing consumers in the "Both" category.

Taking April 2019 and April 2020 as an example, we start with extracting only consumers falling into the "Both" category in both months. Next, for each consumer, we calculate the share of online consumption in April 2019 as the percentage of that consumer's total spending. We calculate the same share for online consumption in April 2020. We divide the interval from 0 to 1 into 10 bins and determine which bin a consumer belongs to in terms of the online consumption share. Then, we define the following conditional probability:

$$\begin{aligned}\hat{a}_{ij} \equiv \Pr(&\text{Online consumption share in April 2020 falls into the } i\text{th bin} \\ &\mid \text{Online consumption share in April 2019 falls into the } j\text{th bin})\end{aligned} \tag{9}$$

where $i, j = 1, 2, \ldots, 10$. We define matrix $\hat{A}$ with the $(i, j)$ element representing the conditional probability $\hat{a}_{ij}$. $\hat{A}$ is similar to $A$ in Section 2.4 but differs from it in that we now focus on the transition of those consumers belonging to the "Both" category in each month.

Similarly, the transition probability matrix $\hat{B}$ can be calculated using the data for January 2019 and January 2020. Finally, denoting the transition probability matrix from January 2020 to April 2020 by $\hat{X}$, we obtain

$$\hat{X} = \hat{A}\hat{B}^{-1} \tag{10}$$

under Assumption $A$ and

$$\hat{X} = \hat{A}\hat{B}^{-3/4} \tag{11}$$

under Assumption $B$.

# 3 Estimation results and implications

The increase in online consumption demand due to the coronavirus shock can be decomposed into (1) the contribution due to the entry of new consumers that had never used the internet for purchases before (i.e., the extensive margin), and (2) the contribution due to the increase in the share of online purchases of those that already made online purchases before (i.e., the intensive margin). Sections 3.1 and 3.2 present the results on the extensive margin and the intensive margin, respectively.

## 3.1 Extensive margin

**Transition probabilities** Panels (d) and (e) of Table 1 show the estimated transition probabilities from January 2020 to April 2020 using equations (7) or (8). The results based on Assumption $A$ in panel (d) indicate that the transition probabilities from "Offline only" to "Both," from "Both" to "Online only," and from "Offline only" to "Online only" are all higher than those in the opposite direction, indicating that more people switched to online consumption during this period. The same pattern can be found in the results based on Assumption $B$.

The transition probabilities from January 2019 to January 2020 shown in panel (a) of Table 1 are the one-year transition probabilities that can be interpreted as representing the transition during a normal period. To compare this to the transition probabilities for January to April 2020, we convert the transition probabilities from January 2019 to January 2020 to a quarterly basis by raising them to the power of 1/4. The results are shown in panel (b) of Table 1, "Transition from January 2019 to January 2020: Quarterly basis."

Comparing panels (d) and (e) with (b) shows the following. First, the transition probability from “Both” to “Online only” is much larger in (d) and (e) than in (b). Specifically, the estimated value from January to April 2020 is 8.7% under Assumption $A$ and 12.5% under Assumption $B$. On the other hand, the probability from January 2019 to January 2020 is only 4.2%. Second, the transition probability from “Offline only” to “Online only” is also larger in (d) and (e) than in (b). While the estimated values from January to April 2020 are 3.2% under Assumption A and 4.2% under Assumption B, the probability from January 2019 to January 2020 is only 0.9%.

These results suggest that many consumers that fell into the “Both” or “Offline only” categories before the pandemic switched to “Online only” to avoid the risk of getting infected with the coronavirus. On the other hand, while the transition probability from “Offline only” to “Both” for January 2020 to April 2020 is larger (6.1% under Assumption $A$ and 9.5% under Assumption $B$) than the transition probability from January 2019 to January 2020 (4.2%), the difference is not that great. Taken together, these results suggest that what many consumers were aiming for amid the spread of COVID-19 was to completely stop shopping offline rather than only going halfway by doing some shopping online.

**Results by gender** Tables 2 and 3 show the same transition probabilities estimated by gender. Looking at the transitions from January 2020 to April 2020 shown in panels (d) and (e) of each table, it is clear that women were more likely than men to switch to online shopping due to the pandemic. Specifically, for each of the transitions from “Offline only” to “Both,” “Both” to “Online only,” and “Offline only” to “Online only,” the transition probabilities for women exceed those for men.

**Results by age** Figure 3 shows the estimation results of the transition probabilities from January to April 2020 by age group. The left panel of the figure shows the transition from “Offline only” to “Both” and vice versa, the middle panel shows the transition from “Both” to “Online only” and vice versa, and the right panel shows the transition from “Offline only” to

**Table 2 Transition probabilities for online consumption: Men**

| | | | | |
|---|---|---|---|---|
| (a) Transition from Jan 2019 to Jan 2020 | | | | |
| | | Jan 2019 | | |
| | | Offline only | Both | Online only |
| Jan 2020 | Offline only | 0.8285 | 0.0350 | 0.0120 |
| | Both | 0.1371 | 0.8333 | 0.1687 |
| | Online only | 0.0343 | 0.1317 | 0.8194 |
| (b) Transition from Jan 2019 to Jan 2020: Quarterly basis | | | | |
| | | Jan 2019 | | |
| | | Offline only | Both | Online only |
| Jan 2020 | Offline only | 0.9534 | 0.0099 | 0.0027 |
| | Both | 0.0389 | 0.9518 | 0.0488 |
| | Online only | 0.0076 | 0.0381 | 0.9484 |
| (c) Transition from Apr 2019 to Apr 2020 | | | | |
| | | Apr 2019 | | |
| | | Offline only | Both | Online only |
| Apr 2020 | Offline only | 0.7645 | 0.0464 | 0.0163 |
| | Both | 0.1709 | 0.7598 | 0.1475 |
| | Online only | 0.0646 | 0.1938 | 0.8362 |
| (d) Transition from Jan 2020 to Apr 2020: Based on Assumption A | | | | |
| | | Jan 2020 | | |
| | | Offline only | Both | Online only |
| Apr 2020 | Offline only | 0.9198 | 0.0165 | 0.0030 |
| | Both | 0.0558 | 0.9108 | -0.0082 |
| | Online only | 0.0242 | 0.0726 | 1.0051 |
| (e) Transition from Jan 2020 to Apr 2020: Based on Assumption B | | | | |
| | | Jan 2020 | | |
| | | Offline only | Both | Online only |
| Apr 2020 | Offline only | 0.8776 | 0.0250 | 0.0062 |
| | Both | 0.0887 | 0.8672 | 0.0367 |
| | Online only | 0.0336 | 0.1077 | 0.9569 |

**Notes**: "Online only" refers to those who make online purchases only, "Both" to those who make both online and offline purchases, and "Offline only" to those who make offline purchases only. Panel (b) shows the results in panel (a) converted to a quarterly basis by raising them to the power of 1/4.

**Table 3 Transition probabilities for online consumption: Women**

| (a) Transition from Jan 2019 to Jan 2020 | | | | |
|---|---|---|---|---|
| | | Jan 2019 | | |
| | | Offline only | Both | Online only |
| Jan 2020 | Offline only | 0.7954 | 0.0479 | 0.0168 |
| | Both | 0.1590 | 0.7853 | 0.1829 |
| | Online only | 0.0456 | 0.1669 | 0.8003 |

| (b) Transition from Jan 2019 to Jan 2020: Quarterly basis | | | | |
|---|---|---|---|---|
| | | Jan 2019 | | |
| | | Offline only | Both | Online only |
| Jan 2020 | Offline only | 0.9432 | 0.0140 | 0.0037 |
| | Both | 0.0468 | 0.9359 | 0.0547 |
| | Online only | 0.0098 | 0.0500 | 0.9414 |

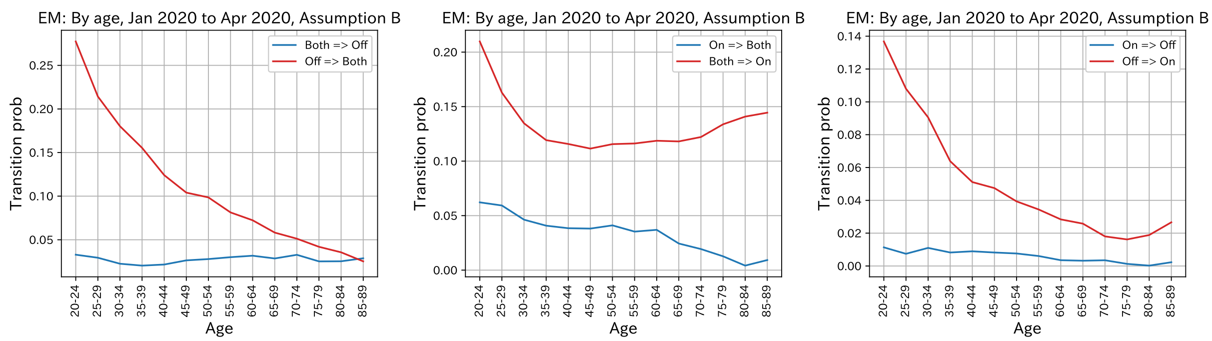
| (c) Transition from Apr 2019 to Apr 2020 | | | | |
|---|---|---|---|---|
| | | Apr 2019 | | |
| | | Offline only | Both | Online only |
| Apr 2020 | Offline only | 0.7093 | 0.0551 | 0.0191 |
| | Both | 0.1936 | 0.6846 | 0.1480 |
| | Online only | 0.0971 | 0.2603 | 0.8329 |

| (d) Transition from Jan 2020 to Apr 2020: Based on Assumption A | | | | |
|---|---|---|---|---|
| | | Jan 2020 | | |
| | | Offline only | Both | Online only |
| Apr 2020 | Offline only | 0.8886 | 0.0156 | 0.0015 |
| | Both | 0.0702 | 0.8708 | -0.0155 |
| | Online only | 0.0411 | 0.1135 | 1.0139 |

| (e) Transition from Jan 2020 to Apr 2020: Based on Assumption B | | | | |
|---|---|---|---|---|
| | | Jan 2020 | | |
| | | Offline only | Both | Online only |
| Apr 2020 | Offline only | 0.8389 | 0.0272 | 0.0057 |
| | Both | 0.1068 | 0.8152 | 0.0333 |
| | Online only | 0.0541 | 0.1575 | 0.9609 |

**Notes**: "Online only" refers to those who make online purchases only, "Both" to those who make both online and offline purchases, and "Offline only" to those who make offline purchases only. Panel (b) shows the results in panel (a) converted to a quarterly basis by raising them to the power of 1/4.

**Figure 3 Transition probabilities for online consumption by age: Jan 2020 to Apr 2020**




**Note**: "On" refers to those who make online purchases only, "Off" to those who make offline purchases only, and "Both" to those who make both online and offline purchases.

"Online only" and vice versa. Note that the results shown here are based on Assumption $B$, but almost the same results are obtained under Assumption $A$ as well.

The three figures have in common that younger people under the age of 35 have a higher probability of turning to online consumption than other age groups. This tendency is particularly noticeable in the transition from "Offline only" to "Both." While most of the young likely were already used to making online purchases before the pandemic to some extent, the findings suggest that even more of them turned to online consumption to avoid getting infected with the coronavirus.

On the other hand, the transition probabilities for older people aged 65 and over are extremely low both for the transition from "Offline only" to "Both" shown in the left panel and the transition from "Offline only" to "Online only" shown in the right panel and in fact are not very different from the transition probabilities in the opposite direction represented by the blue line. Note that the blue line has almost the same values for different age groups, implying that it can be regarded as representing the size of noise contained in the data. This means that the transition probabilities both from "Offline only" to "Both" and from "Offline only" to "Online only" for seniors can be regarded as being close to zero. These results suggest that seniors are more likely to be unfamiliar with making online purchases than the young and that the pandemic did not prompt such seniors to start making online purchases.

Where the transition probability for seniors over the age of 65 is high is in the transition from "Both" to "Online only" shown in the middle panel.[12] Interestingly, after age 70, the red line in the figure increases slightly with age. This can be regarded as indicating that some seniors were familiar with making online purchases before the pandemic and that among them those that were sensitive to the risk of corona infection completely stopped shopping offline to avoid that risk.

**Results for goods consumption and services consumption** Tables 4 and 5 show the results of estimating the transition probabilities by dividing consumption into goods consumption and services consumption. Starting with goods consumption, comparing the transition probabilities from January 2020 to April 2020 with those from January 2019 to January 2020 shows a high transition probability from "Both" to "Online only." Specifically, the estimates for January to April 2020 are 7.6% for Assumption $A$ and 10.9% for Assumption $B$, while for January 2019 to January 2020 the value is 3.6%. Moreover, the transition probability from "Offline only" to "Online only" is also high. The estimates for January to April 2020 are 2.6% for Assumption $A$ and 3.6% for Assumption $B$, while the value for January 2019 to January 2020 is 0.7%. On the other hand, although the transition probability from "Offline only" to "Both" for January to April 2020 is higher than that for January 2019 to January 2020, the difference is relatively small. These results are similar to those found in Table 1 for overall consumption.

Turning to services consumption, the transition probability from "Both" to "Online only" is very high. The estimates for January 2020 to April 2020 are 28.3% under Assumption $A$ and 33.6% under Assumption $B$ and thus more than three times as large as the probability for January 2019 to January 2020 (7.6%). On the other hand, the transition probabilities from "Offline only" to "Both" and from "Offline only" to "Online only" are not very different

[12] That said, the pattern that the probability rises with age is not found in the results based on Assumption $A$.

from the probability for January 2019 to January 2020. Whereas the consumption of services involving close proximity to others, such as cinemas, theaters, and eating out, decreased sharply with the spread of coronavirus infections, spending on online services such as online streaming of movies and television series continued to increase. Our results suggest that the dominant factor in this change was that consumers that used to make both online and offline purchases switched to making online purchases only.

**Table 4 Transition probabilities for online consumption: Goods consumption**

| (a) Transition from Jan 2019 to Jan 2020 | | | | |
|---|---|---|---|---|
| | | Jan 2019 | | |
| | | Offline only | Both | Online only |
| Jan 2020 | Offline only | 0.8011 | 0.1723 | 0.0716 |
| | Both | 0.1658 | 0.7156 | 0.2249 |
| | Online only | 0.0331 | 0.1121 | 0.7034 |
| **(b) Transition from Jan 2019 to Jan 2020: Quarterly basis** | | | | |
| | | Jan 2019 | | |
| | | Offline only | Both | Online only |
| Jan 2020 | Offline only | 0.9416 | 0.0529 | 0.0163 |
| | Both | 0.0510 | 0.9109 | 0.0725 |
| | Online only | 0.0074 | 0.0362 | 0.9112 |
| **(c) Transition from Apr 2019 to Apr 2020** | | | | |
| | | Apr 2019 | | |
| | | Offline only | Both | Online only |
| Apr 2020 | Offline only | 0.7216 | 0.1321 | 0.0470 |
| | Both | 0.2100 | 0.6890 | 0.1786 |
| | Online only | 0.0685 | 0.1790 | 0.7744 |
| **(d) Transition from Jan 2020 to Apr 2020: Based on Assumption A** | | | | |
| | | Jan 2020 | | |
| | | Offline only | Both | Online only |
| Apr 2020 | Offline only | 0.9079 | -0.0315 | -0.0155 |
| | Both | 0.0667 | 0.9559 | -0.0586 |
| | Online only | 0.0255 | 0.0757 | 1.0741 |
| **(e) Transition from Jan 2020 to Apr 2020: Based on Assumption B** | | | | |
| | | Jan 2020 | | |
| | | Offline only | Both | Online only |
| Apr 2020 | Offline only | 0.8532 | 0.0187 | -0.0017 |
| | Both | 0.1111 | 0.8722 | 0.0170 |
| | Online only | 0.0358 | 0.1091 | 0.9847 |

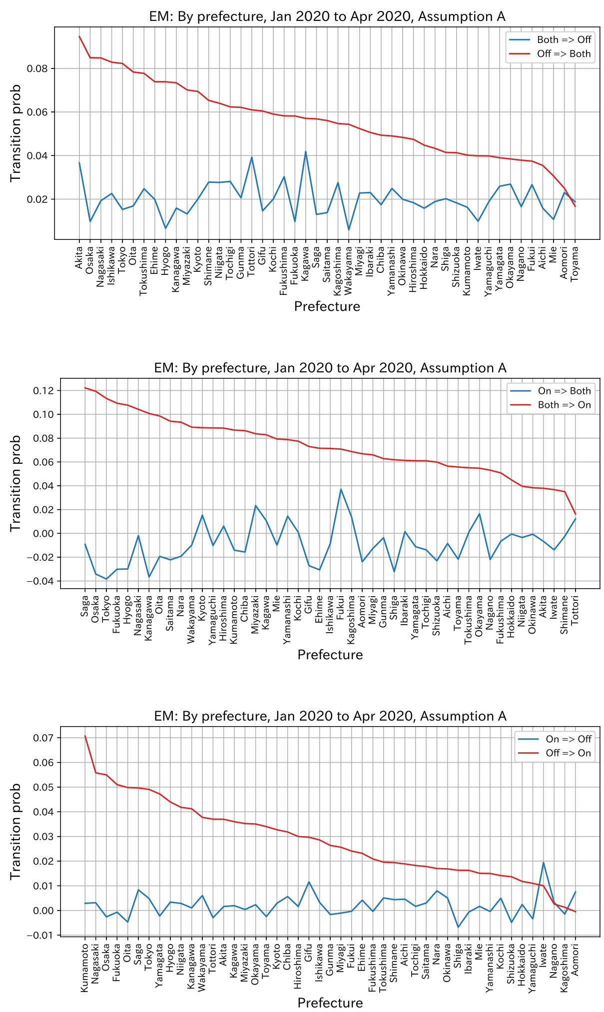
**Notes**: "Online only" refers to those who make online purchases only, "Both" to those who make both online and offline purchases, and "Offline only" to those who make offline purchases only. Panel (b) shows the results in panel (a) converted to a quarterly basis by raising them to the power of 1/4.

**Table 5 Transition probabilities for online consumption: Services consumption**

| (a) Transition from Jan 2019 to Jan 2020 | | | | |
|---|---|---|---|---|
| | | Jan 2019 | | |
| | | Offline only | Both | Online only |
| Jan 2020 | Offline only | 0.7114 | 0.0317 | 0.0092 |
| | Both | 0.1816 | 0.7174 | 0.1319 |
| | Online only | 0.1071 | 0.2509 | 0.8589 |
| **(b) Transition from Jan 2019 to Jan 2020: Quarterly basis** | | | | |
| | | Jan 2019 | | |
| | | Offline only | Both | Online only |
| Jan 2020 | Offline only | 0.9173 | 0.0100 | 0.0022 |
| | Both | 0.0571 | 0.9143 | 0.0398 |
| | Online only | 0.0255 | 0.0757 | 0.9580 |
| **(c) Transition from Apr 2019 to Apr 2020** | | | | |
| | | Apr 2019 | | |
| | | Offline only | Both | Online only |
| Apr 2020 | Offline only | 0.6927 | 0.0540 | 0.0121 |
| | Both | 0.1353 | 0.4883 | 0.0803 |
| | Online only | 0.1719 | 0.4576 | 0.9075 |
| **(d) Transition from Jan 2020 to Apr 2020: Based on Assumption A** | | | | |
| | | Jan 2020 | | |
| | | Offline only | Both | Online only |
| Apr 2020 | Offline only | 0.9656 | 0.0330 | -0.0013 |
| | Both | 0.0174 | 0.6841 | -0.0117 |
| | Online only | 0.0171 | 0.2829 | 1.0130 |
| **(e) Transition from Jan 2020 to Apr 2020: Based on Assumption B** | | | | |
| | | Jan 2020 | | |
| | | Offline only | Both | Online only |
| Apr 2020 | Offline only | 0.8876 | 0.0398 | 0.0022 |
| | Both | 0.0547 | 0.6247 | 0.0160 |
| | Online only | 0.0577 | 0.3355 | 0.9818 |

**Notes**: “Online only” refers to those who make online purchases only, “Both” to those who make both online and offline purchases, and “Offline only” to those who make offline purchases only. Panel (b) shows the results in panel (a) converted to a quarterly basis by raising them to the power of 1/4.

## Figure 4 Transition probabilities for online consumption by prefecture: Jan 2020 to Apr 2020




**Note**: "On" refers to those who make online purchases only, "Off" to those who make offline purchases only, and "Both" to those who make both online and offline purchases.

**Results by prefecture** Figure 4 shows the results of estimating the transition probabilities from January to April 2020 by prefecture. The upper panel of Figure 4 shows the transition from "Offline only" to "Both" and vice versa, the middle panel shows the transition from "Both" to "Online only" and vice versa, and the lower panel shows that from "Offline only" to

“Online only” and vice versa. The results shown here are based on Assumption $A$, but almost identical results are obtained under Assumption $B$.

The three panels suggest the following. First, comparing the scale on the vertical axis in Figure 4 with that of Figure 3 indicates that while the variation in transition probabilities across prefectures is not zero, it is much smaller than the variation across generations. Second, among the prefectures with the highest transition probabilities in the three panels are urban areas such as Tokyo, Osaka, Kanagawa, and Hyogo. On the other hand, Akita (a rural prefecture in the north of Honshu), for example, is at the top in the transition from “Offline only” to “Both” shown in the upper panel, but it is not among the top-ranked in the middle and lower panels. Based on these results, it cannot be said that consumers in Akita were more likely to turn to online shopping than those in other prefectures.[13]

One reasons why urban areas such as Tokyo are among the top prefectures likely is that younger generations make up a large population share. As seen in Figure 3, there is a close link between age and transition probabilities, and the results by prefecture may reflect this. Another potential reason is that the severity of the spread of coronavirus infections varies across prefectures. In urban areas such as Tokyo, the spread of infections was more serious, and consumers were more likely to avoid contact with others. Yet another factor leading consumers in urban areas to turn to online consumption likely is that the degree to which local governments requested people to stay at home and avoid physical stores was stronger in urban areas.[14]

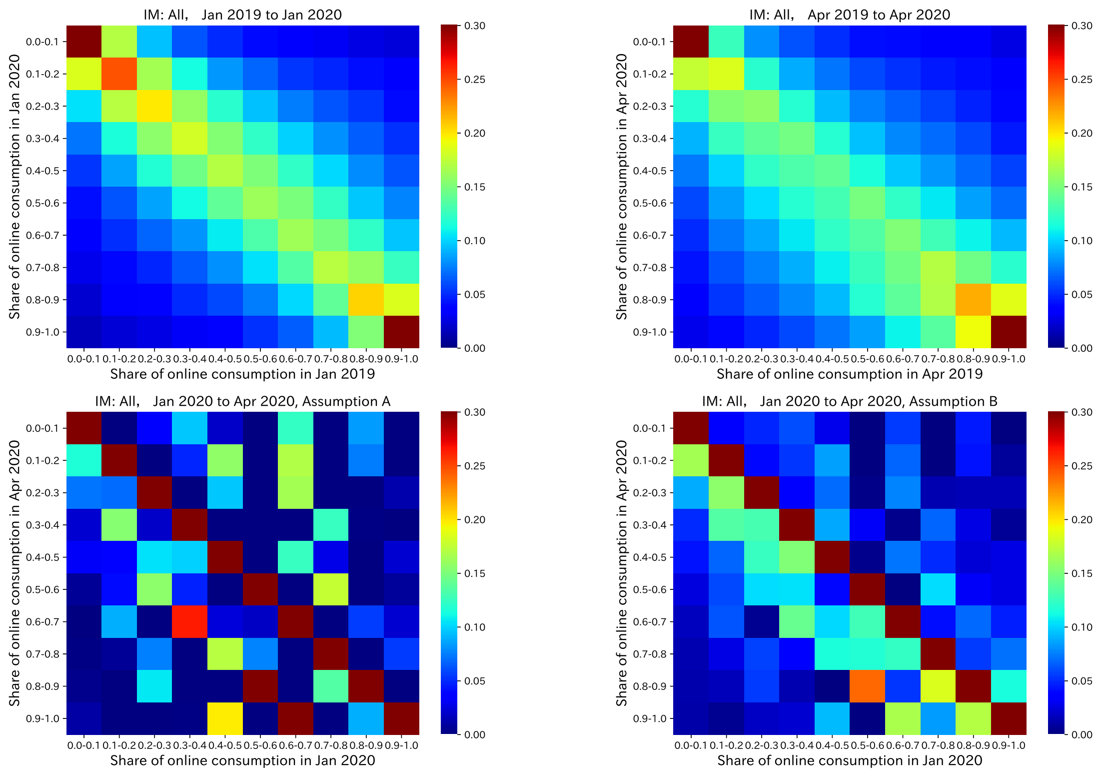
### 3.2 Intensive margin

**Transition probabilities** Figure 5 shows the estimation result of the transition probability matrices for the share of online consumption in consumers’ total spending. The upper left matrix in Figure 5 shows the transition from January 2019 to January 2020 ($\hat{B}$), while the

[13]Similarly, in the transition from “Both” to “Online only” shown in the middle panel, Saga (another non-urban prefecture, located in Kyushu) is at the top, but in the other panels it is not among the top prefectures. Moreover, Kumamoto (another non-urban prefecture in Kyushu) is at the top in the transition from “Offline only” to “Both” shown in the lower panel, but it is not among the top prefectures in the other panels.

[14][See Watanabe and Yabu (2020) for mitigations measures taken by the national and local governments in Japan and their impact on peoples’ behavior.

**Figure 5 Transition probabilities for the share of online consumption**

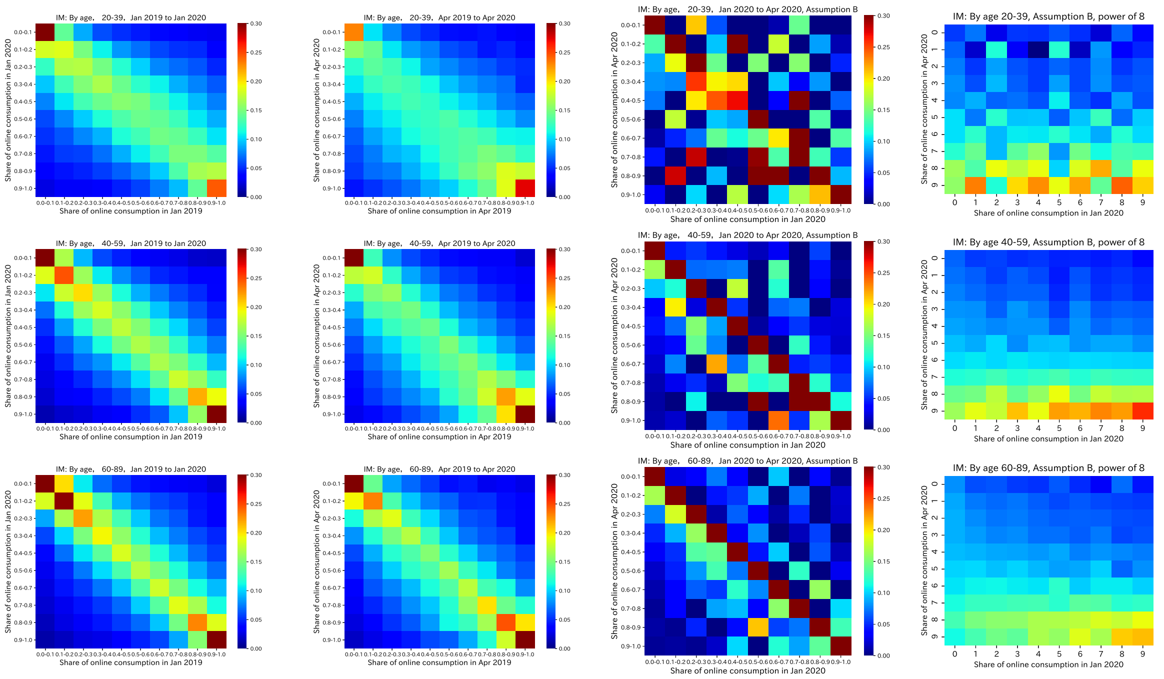



**Note**: Probabilities greater than 0.3 are represented by the same color as 0.3.

upper right matrix shows the transition from April 2019 to April 2020 ($\hat{A}$). In both matrices the diagonal elements show high transition probabilities, indicating that for many consumers the share of online consumption has remained unchanged from a year earlier. Comparing $\hat{B}$ with $\hat{A}$ shows that whereas the probabilities of off-diagonal elements in $\hat{B}$ are symmetric about the diagonal, in $\hat{A}$ probabilities are higher below the diagonal. This indicates that, as of April, many consumers had increased their online consumption share compared to a year earlier, reflecting the impact of the pandemic.

The lower part of Figure 5 shows the results for the transition probabilities from January 2020 to April 2020. The left matrix represents the results under Assumption $A$, while the right matrix shows those under Assumption $B$. Looking at the results under Assumption $B$, there

**Figure 6 Transition probabilities for the share of online consumption by age**




**Note**: Probabilities greater than 0.3 are represented by the same color as 0.3.

is a clear tendency for the probabilities to be higher below the diagonal, suggesting that many consumers increased the share of online purchases due to the pandemic. Taking a closer look at the part below the diagonal shows that consumers with a high share of online purchases as of January 2020 tended to increase their share as of April 2020. In other words, consumers that relied heavily on online purchases before the pandemic increased their online consumption share even further.[15]

**Results by age** Figure 6 shows the results of estimating the transition probability matrices for online consumption shares by age group. The top row shows the results for the young (aged 20-39 years), the middle row shows those for the middle-aged (aged 40-59), and the bottom

[15]Although a clear pattern cannot be visually discerned from the results under Assumption $A$, when looking at the actual numbers, a comparison of the figures above and below the diagonal shows that the probabilities below the diagonal are higher, indicating that it was consumers that already did make a large share of their purchases online to begin with that increased their share of online purchases.

row is for seniors (60-89).

Starting with the middle-aged, compared to the matrix for January 2019 to January 2020 (first matrix in the middle row), in the matrix for April 2019 to April 2020 (second matrix in the middle row) the transition probabilities decline in the diagonal and instead increase immediately below the diagonal. This indicates that there were many consumers that increased their online consumption share due to the pandemic. In the matrix for January 2020 to April 2020 (third matrix in the middle row), too, the probabilities are higher below than above the diagonal. Taking a closer look at the part below the diagonal shows that consumers with a high share of online consumption as of January 2020 tended to have increased their share as of April 2020. All of these features are essentially the same as those observed in Figure 5.

Next, looking at the results for seniors, the probabilities in the diagonal elements of the second matrix in the bottom row are lower than in the first matrix in the bottom row, and the probabilities below the diagonal have increased instead. Moreover, the third matrix shows the same pattern as that for the middle-aged, although it is weaker than for the middle-aged.

Finally, looking at the young, the transition matrix for April 2019 to April 2020 in the second column in the top row shows that compared with the matrix for January 2019 to January 2020 the probabilities in the diagonal elements declined, which is similar to the result for the middle-aged and seniors. However, for the off-diagonal elements, unlike for the middle-aged and seniors, it is not possible to visually ascertain that the probabilities below the diagonal are higher than those above the diagonal. Also, in the transition matrix for January 2020 to April 2020 in the third column, no clear correlation between the values for January 2020 and the values for April 2020 can be observed.

To show how the results for the young differ from those for the other two age groups, the far right column presents the matrices in the third column raised to the power of 8. In other words, it looks at what would happen if the three-month transition from January 2020 to April 2020 lasted for 24 months. Cells with high probability values are concentrated in the lower part of the matrix, meaning that the online consumption share for most consumers approaches 1 after 24 months. However, comparing the matrix for the young with those for the middle-aged and seniors shows that more middle-aged and senior consumers are near an online ratio of 1. This indicates that the speed at which young consumers switched to online consumption due to the pandemic is much slower than middle-aged and senior consumers.[16]

## 4 Forecasts

In the previous section, we examined the transition matrix estimation results. In this section, we use the estimated transition probability matrices to forecast future online consumption. Specifically, we forecast how the prevalence of online consumption, that is, the shares of consumers falling into the "Offline only," "Both," and "Online only," will change in the future.

The premise of our forecast is the assumption that the risk of coronavirus infection disappears in October 2021, followed by a period of no risk of infection (for example, due to the development of COVID-19 vaccines). Concretely, for our forecast, we regard January 2020 (i.e., before the spread of COVID) as the starting point ($t = 0$) and April 2020 ($t = 1$), July 2020 ($t = 2$), October 2020 ($t = 3$), January 2021 ($t = 4$), April 2021 ($t = 5$), July 2021 ($t = 6$) as the period when there was a high risk of infection. Further, we assume that infections will subside by October 2021 ($t = 7$) and that from January 2022 ($t = 8$) there will be no new infections. Based on this setting, we calculate the share of consumers falling into the "Offline only," "Both," and "Online only" categories for $t = 0, 1, 2, \ldots, 6$ using actual data and forecast those shares for $t = 7$ and later.

The column vector $s_t$ is used to represent the shares of consumers falling into the "Offline only," "Both," and "Online only" categories at time $t$. The vectors $s_1$, $s_2$, …, $s_6$ consist of actual values and can be written as

$$\begin{aligned} &s_1 = X_{\text{Apr20}} s_0; \quad s_2 = X_{\text{Jul20}} s_1; \quad s_3 = X_{\text{Oct20}} s_2 \\ &s_4 = X_{\text{Jan21}} s_3; \quad s_5 = X_{\text{Apr21}} s_4; \quad s_6 = X_{\text{Jul21}} s_5 \end{aligned} \tag{12}$$

where $X_{\text{Apr20}}$ is the transition matrix from January 2020 to April 2020, which was denoted by

[16] See Omori and Watanabe (2020) for more results on the intensive margin.

$X$ in the previous sections, and $X_{\text{Jul20}}$ to $X_{\text{Jul21}}$ are defined similarly. Using equation (12), $s_6$ can be written as

$$
\begin{aligned}
s_6 &= Z s_0 \\
&= \left(Z - B^{6/4}\right) s_0 + B^{6/4} s_0
\end{aligned}
\tag{13}
$$

where $Z$ is defined by $Z \equiv X_{\text{Jul21}} X_{\text{Apr21}} X_{\text{Jan21}} \times \cdots \times X_{\text{Apr20}}$, representing the transition matrix from January 2020 to July 2021. Matrix $B$ is the transition matrix from January 2019 to January 2020 and represents the transition during normal times. The first term on the right-hand side of equation (13) represents the shock associated with the coronavirus pandemic in the first three periods. The coronavirus shock can be further decomposed as follows:

$$
\left(Z - B^{6/4}\right) s_0 = \underbrace{\begin{pmatrix} z_{11} - b_{11}^{6q} & 0 & 0 \\ z_{21} - b_{21}^{6q} & 0 & 0 \\ z_{31} - b_{31}^{6q} & 0 & 0 \end{pmatrix} s_0}_{\text{Persistent component of the coronavirus shock}} + \underbrace{\begin{pmatrix} 0 & z_{12} - b_{12}^{6q} & z_{13} - b_{13}^{6q} \\ 0 & z_{22} - b_{22}^{6q} & z_{23} - b_{23}^{6q} \\ 0 & z_{32} - b_{32}^{6q} & z_{33} - b_{33}^{6q} \end{pmatrix} s_0}_{\text{Transitory component of the coronavirus shock}}
\tag{14}
$$

where $z_{ij}$ and $b_{ij}^{6q}$ are the $(i, j)$ elements of $Z$ and $B^{6/4}$, respectively.

As mentioned in Section 1, reasons pointed out why consumers who have never used the internet to make purchases are hesitant to start doing so include the following: (1) the upfront costs of going online, (2) concern that their personal information might be leaked, and (3) information asymmetries on the quality of goods and services. However, consumers that started to use the internet for shopping and services during the coronavirus pandemic have already paid the upfront costs, and their concerns about the leakage of personal information and the quality of goods and services may have been dispelled by their actual experience of using the internet for purchases. If the pandemic has an irreversible effect on online consumption, it will be through this channel. In the following, to reflect this channel in the forecasts for online consumption, we make the following assumptions for the first and second terms on the right-hand side of (14).

To start with, looking at the first term on the right-hand side, this shows where consumers that fell into the "Offline only" category in period 0 transitioned due to the coronavirus shock and how much $s_6$ changed as a result. Since these consumers had not used the internet for purchases before the pandemic, where they transitioned to in the first period affects the results from the second period onward; in other words, we assume that the first term on the right-hand side of (14) is a persistent shock.

On the other hand, the second term on the right-hand side of (14) represents where consumers that fell into the "Both" or "Online only" categories in period 0 transitioned during the shock and hence how much $s_6$ changed as a result. Since these consumers had used the internet for purchases before the pandemic, we assume that where such consumers transition in period 1, and how $s_6$ changes as a result, does not affect $s_t$ in period 7 and later. Therefore, the second term on the right-hand side of (14) can be regarded as a transient shock.

Under the above assumptions, the second term on the right-hand side of equation (14) does not affect $s_7$. Therefore, $s_7$ can be expressed as follows:

$$s_7 = B^{1/4}\left[\begin{pmatrix} z_{11} - b_{11}^{6q} & 0 & 0 \\ z_{21} - b_{21}^{6q} & 0 & 0 \\ z_{31} - b_{31}^{6q} & 0 & 0 \end{pmatrix} s_0 + B^{6/4} s_0\right] = B^{1/4}\begin{pmatrix} z_{11} & b_{12}^{6q} & b_{13}^{6q} \\ z_{21} & b_{22}^{6q} & b_{23}^{6q} \\ z_{31} & b_{32}^{6q} & b_{33}^{6q} \end{pmatrix} s_0 \tag{15}$$

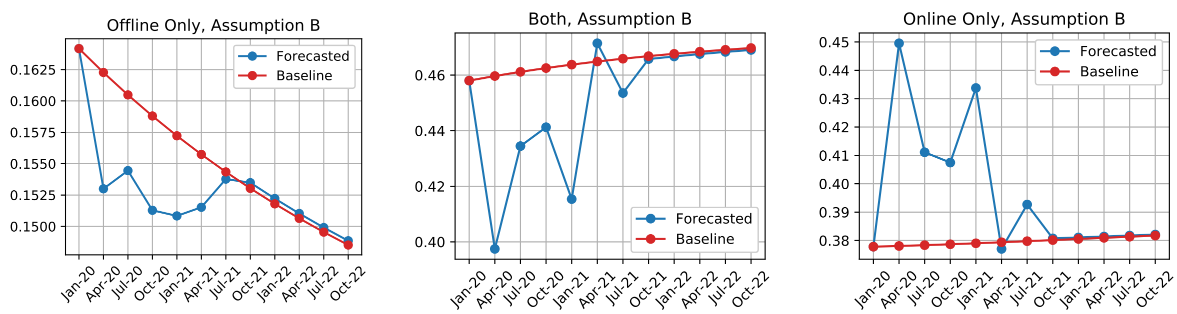
Finally, $s_t$ $(t = 8, 9, \ldots)$ can be calculated using the following equation:

$$s_t = \left(B^{1/4}\right)^{t-7} s_7 \tag{16}$$

Figure 7 shows the forecast results using equations (15) and (16). The blue lines in the panels represent the forecasted values, while the red lines show the counterfactual values; i.e., the values that would be obtained if the transition continued to follow the trend before the coronavirus shock ($s_t = \left(B^{1/4}\right)^t s_0$ for $t = 0, 1, 2, \ldots$).

Beginning with the results for April 2020 ($t = 1$), the start period of the COVID-19 pandemic in Japan, we find that the share of consumers falling into the "Online only" category increased substantially. The share of "Online only" is 45%, and the deviation from the baseline shown by the red line is 7 percentage points. On the other hand, the share of consumers falling into the "Both" category decreased sharply, falling 6 percentage points below the baseline. This shows that due to the coronavirus shock, the share of consumers falling into the "Both"

**Figure 7  Forecast of online purchasing behavior**




**Notes**: The left column shows the share of consumers falling into the "Offline only" category, the middle column those falling into the "Both" category, and the right column those falling into the "Online only" category. The results are based on Assumption B for $X$. The blue lines show the actual values for $t = 0$ (Jan 2020) to $t = 6$ (Jul 2021), and the forecasts for $t = 7$ and subsequent periods calculated using equations (15) and (16). The red lines are calculated using $s_t = \left(B^{1/4}\right)^t s_0$ and represent the baseline assuming that online consumption behavior had continued to follow the trends observed until January 2020.

category declined and there was a corresponding increase in consumers falling into the "Online only" category. On the other hand, although the share of consumers falling into the "Offline only" category decreased, the size of the decrease relative to the baseline is only 1 percentage points. We can therefore say that not many consumers transitioned in April 2020 from "Offline only" to "Online only." The share of "Online only" consumers shows a gradual decline in July 2020 and October 2020, which is mostly accounted for by the corresponding increase in the share of "Both" consumers.

The fact that most of the increase in "Online only" consumers in April 2020 and the subsequent periods came from the transition of consumers in the "Both" category has important implications for the forecast for October 2021 ($t = 7$). As explained in equation (14), the transition from "Both" to "Online only" is a transient shock associated with the pandemic and does not affect the shares in October 2021 and later. On the other hand, although the transition from "Offline only" to "Online only" was a persistent shock, the share of consumers making this transition was very small, so that the shock is also very small. Reflecting these two properties, the forecast for "Online only" in October 2021 falls back sharply. Although the "Online only" share for October 2021 continues to be slightly higher than the baseline, the difference is negligible. In sum, it is highly likely that online consumption activity will return to the level before the pandemic.

## 5 Conclusion

With the spread of novel coronavirus infections, people's consumption patterns have changed dramatically. While demand for services that involve face-to-face contact, such as eating out and entertainment, has decreased sharply, online consumption of goods and services such as e-commerce has increased, and some expect such patterns to continue once the pandemic subsides. In this paper, using credit card transaction data, we examined whether the increase in online consumption will persist once the pandemic has subsided.

Online consumption requires upfront costs such as the purchase of devices, maintaining internet access, and acquiring know-how, and such costs are regarded as one of the factors impeding the spread of online consumption. In addition, there are strong concerns about the potential leakage of personal information and the inability to check the quality of products and services before buying them. These factors are also said to impede the spread of online consumption. However, if the coronavirus outbreak led many consumers to make these upfront investments, they would have no reason to return to offline consumption after the pandemic. In addition, it is possible that actually using the internet for purchases during the pandemic may have dispelled the various concerns. Given this, one would expect online consumption "novices" to continue to use the internet for purchases even when the risk of getting infected with the coronavirus has disappeared.

The main findings of this paper are as follows. First, the main group responsible for the increase in online consumption during the coronavirus period were consumers who were already familiar with online consumption before the pandemic and purchased goods and serviced both online and offline. The fact that any of these consumers stopped all their offline consumption and switched to online only consumption substantially contributed to the increase in online consumption. Second, there were some consumers that had never used the internet for purchases before and that started to do so during the pandemic, but the share of such consumers was limited. Third, by age group, the switch to online consumption was more pronounced among youngsters than seniors. The difference between the age groups in terms of switching to online consumption is not due to differences in digital literacy but likely reflects differences in attitudes with regard to the risk of infection.

Further, based on these findings, we attempted to forecast online consumption after the pandemic subsides. The increase in online consumption during the coronavirus period is due to the increase in online consumption among consumers that already were used to making purchases online and that were worried about the risk of infection. The level of online consumption of these consumers is likely to return to pre-pandemic levels as the risk of infection recedes. Thus, while it is widely argued that the changes in consumers' behavior due to the coronavirus shock are irreversible, the forecast results obtained in this paper suggest that the increase in online consumption is not irreversible.

In this paper, we focused on the switching costs from offline consumption to online consumption as the reason why the increase in online consumption might be irreversible and conducted our analysis based on the assumption that these costs are particularly high for consumers that have never been online. However, some argue that in the post-coronavirus era, social and economic customs will change substantially, and we recognize that this could clearly have an effect on online consumption. As data gradually become available in the future for the period in which the risk of infection is reduced, further investigation into whether the shift to online consumption is irreversible or not and the reasons will be necessary.

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