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Abstract

Online consumption in Japan has increased significantly since the outbreak of the COVID-19 pandemic. However, many issues remain unclear, such as what kind of households have increased their online consumption and whether the increase in online consumption is temporary or highly persistent. In this paper, we provide an empirical analysis of online consumption trends during the pandemic, using (i) granular tailor-made data from the *Survey of Household Economy* by the Ministry of Internal Affairs and Communications and (ii) aggregated figures computed from transaction data from "Money Forward ME," the personal financial management service provided by Money Forward, Inc. Our empirical results based on these datasets up to December 2020 show that online consumption in Japan increased among a wide range of age and income groups, that many households engaged in online consumption for the first time during the pandemic, and that most of these households continued to engage in online consumption. While it should be noted that the results are based on a limited observation period, they suggest that the increase in online consumption likely is highly persistent. If such changes in household behavior are indeed highly persistent, they may have important implications for Japan's economy.

JEL classification: D12, E21.

Keywords: Online Consumption, COVID-19, Alternative Data.

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1. Introduction

The outbreak of the COVID-19 pandemic in 2020 led to severe restrictions on people's behavior through a range of public health measures. Such restrictions have transformed people's economic activities, and some of the effects appear to be lasting even as the impact of the pandemic recedes. A key question therefore is whether the behavioral changes brought about by the pandemic are temporary or highly persistent, which has potentially important implications for Japan's economy after the pandemic.

Among the changes in economic activity caused by the pandemic, one of the most notable changes is the expansion of online consumption, which has been observed in countries around the world. The Bank of England (2020), for instance, highlights that online consumption in the United Kingdom increased significantly following the outbreak of COVID-19. Meanwhile, analyzing changes in consumption behavior after the outbreak of COVID-19 using payment transaction data for about 70 million payment cards issued in France, Bounie *et al.* (2020) find that online consumption in France increased significantly, offsetting some of the decline in offline consumption. Similarly, investigating online consumption trends and differences across age groups in the Czech Republic, Jílková and Králová (2021) show that while online consumption increased among all age groups, the main driving force of the increase in overall online consumption was the baby-boomer generation (those born between 1946 and 1964).

Turning to Japan, examining online consumption using credit card data from "JCB Consumption NOW," Watanabe and Omori (2021) show that online consumption in Japan increased substantially during the pandemic. Their analysis indicates that this increase is mainly attributable to a rise in the share of online spending in total spending of those already shopping and consuming online, while the number of those new to online consumption increased only at the same rate as before the pandemic. The authors argue their result implies that the marked increase in total online consumption during the pandemic is temporary and that online consumption is likely to return to previous trends as the effect of COVID-19 wanes. To the best of our knowledge, their paper is one of the only studies examining online consumption trends in Japan during the pandemic, and there is little other evidence to assess whether the increase in online consumption in Japan is temporary or highly persistent, partly because of the limited availability of official statistics providing comprehensive data that would allow a detailed analysis of online consumption trends.

Against this background, the present study provides empirical analyses of online consumption trends in Japan during the COVID-19 pandemic using so-called alternative data[1] to find that online consumption did increase substantially following the outbreak of COVID-19. In addition, we investigate whether the increase in online consumption is temporary or highly persistent.

Watanabe and Omori (2021) argue that when examining whether the increase in online consumption is temporary or highly persistent, it is useful to decompose the increase into the increase due to a rise in the share of online consumption in the total consumption of existing online consumers (i.e., the intensive margin) and the increase due to the increase in those new to online consumption (i.e., the extensive margin). If the main driver of the increase in online consumption is the increased share of online consumption among those that already regularly engaged in online consumption before the pandemic, the boost to online consumption observed during the pandemic may have been only temporary, if such consumers revert to their consumption before the pandemic. In contrast, if individuals that had been hesitant to shop and consume online due to the associated "entry costs" (such as the direct costs of purchasing a digital device and setting up online access, and the opportunity costs of learning how to use a digital device and setting up user accounts) before the pandemic started to engage in online consumption during the pandemic, some of these individuals may continue with online consumption (e.g., due to the convenience), so that their consumption patterns may not revert to those before the pandemic.

In this paper, we use two datasets: a granular tailor-made dataset based on the *Survey of Household Economy* (hereafter, HE Survey) by the Ministry of Internal Affairs and Communications, and a dataset based on transaction data provided by Money Forward, Inc., a company that provides online personal financial management services via a website and a smartphone app. We refer to this as the "MF dataset." The HE Survey is one of the few official statistics containing time series of online consumption in Japan. The survey asks participating households nationwide how much they spent online each month on different spending categories. The publicly available version of the HE Survey dataset only contains aggregated figures for different household groups stratified by, for example, age, annual income, and region. For this study, we ordered a tailor-made dataset based on the HE Survey from the National Statistics Center, which includes disaggregated series on online consumption based on a finer stratification in terms of combinations of region, age, and annual income.

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[1] Here, "alternative data" refers to data other than conventional statistics published by official bodies such as government agencies. An overview of analyses by the Bank of Japan using alternative data can be found in Kameda (2022). In addition, the Bank of Japan has set up an "Alternative Data Analysis" section on its website to post related research.

The MF dataset consists of aggregated figures computed from transaction data from "Money Forward ME," the personal financial management service provided by Money Forward, Inc. For our analysis, we use time series data on the monthly total spending and online spending of different age groups. There are very few studies using this kind of data for economic analyses[2] and, as will be explained later, it is necessary to pay close attention to the sample characteristics of the dataset, since it does not come from a statistical survey collected for the purpose of economic analysis.

The MF dataset has the advantage that it provides information that is not available in official statistics. For instance, unlike the HE Survey, the MF dataset captures individual households' total spending, including their offline spending, making it possible to calculate the share of households' e-commerce (EC) spending in total spending (which we refer to as the EC share below). Another important advantage is that the dataset makes it easy to identify changes in consumption activities at the individual household level.

Meanwhile, based on the empirical results on online consumption obtained in this study, we also discuss the potential course of online consumption trends in the post-pandemic era and the impact they might have on the Japanese economy. Specifically, conducting additional empirical analyses, we consider the impact that the increase in online consumption could have on business fixed investment and consumer prices.

The remainder of this paper is organized as follows. Section 2 describes our analysis using the HE Survey data, while Section 3 presents the analysis using the MF dataset. Section 4 discusses the impact of increased online consumption on other economic activities. Section 5 concludes.

2. Analysis using the Survey of Household Economy

2.1. Data

The HE Survey is a monthly survey conducted by the Ministry of Internal Affairs and Communications since 2002 with the aim of grasping private consumption trends and those of online purchases in Japan. The survey covers about 30,000 households throughout Japan. Regarding online consumption, continuous time-series data can be obtained from January 2015, providing information on the amount of online spending each month and a breakdown

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[2] One of the few studies to do so is that by Kaneda *et al.* (2021), who use a different dataset based on transactions in Money Forward ME to investigate the impact on household consumption of the Special Cash Payments provided by the Japanese government to households in 2020 as part of the emergency measures to cope with COVID-19.

by item category. In addition, the survey includes information on the share of households that engaged in online consumption at least once during the month in total households.

The publicly available data of the survey only include aggregated figures for different household groups, classified, for example, by age (of the head of household), annual income level (of the entire household), and region. For the current study, to conduct a detailed analysis, we requested the National Statistics Center to compile a dataset of tailor-made statistics from the HE Survey including disaggregated series on online consumption with a finer mesh of combinations of regions, age, and annual income levels for the period from 2015 to 2020.

In this analysis, we define "EC households" as households that spent online at least once in a particular month. Using this definition, we mainly focus on two variables: (i) the EC household share, i.e., the share of EC households in the total number of households, and (ii) EC spending per EC household (referred to as "EC spending" hereafter unless otherwise specified), which is calculated using the "total expenditure using the Internet" and the EC household share. As mentioned above, because the HE Survey does not contain information on households' total expenditure including offline spending, the EC share, i.e., the share of EC spending in the total spending of households that engage in online spending, cannot be calculated.

In the analysis, we exclude online spending on services such as ticket purchases and travel reservations. The reason is that our analysis focuses on economic developments during the COVID-19 pandemic, during which online purchases of goods expanded while spending on services such as travel and tickets for sports events, movies, and concerts fell substantially due to COVID-19. The HE Survey includes a breakdown of "total spending using the Internet" by item category. This allows us to subtract "accommodation charges, fares, package travel expenses" and "tickets" from "total spending using the Internet" to obtain EC spending.

2.2. Online consumption trends: An overview

Chart 1 shows developments in (a) the EC household share and (b) EC spending based on the HE Survey. The EC household share has been on an increasing trend, rising from less than 30% in 2015 to around 45% at the beginning of 2020, i.e., just before the COVID-19 pandemic. Since then, the EC household share has jumped considerably, reaching a level of more than 50% in the latter half of 2020. The dashed line in the figure shows the linear trend from the beginning of 2015 to the January-March quarter of 2020 and highlights that since the start of the pandemic the EC household share has climbed above the trend line.

EC spending has also been on a gradual uptrend since 2015. Since the April-June quarter in 2020, when the pandemic got severe and the Japanese government declared a state of emergency, EC spending rose above the trend in the pre-COVID-19 period. While before COVID-19 monthly EC spending was about 24,000 yen per EC household, it has reached more than 30,000 yen since the start of the pandemic.

Using our tailor-made statistics, which are more granular than publicly available statistics, we examine whether these notable changes in online consumption likely are temporary or highly persistent.

2.3. Estimation methodology

We estimate the following panel regression to examine the change in online consumption during the COVID-19 pandemic:

$$y_{ijkt} = c + q \cdot t + a \cdot z_{it} + b \cdot s_t + \boldsymbol{\gamma} \cdot \boldsymbol{d}_{jkt} + \varepsilon_{ijkt},$$

where y_{ijkt} is the dependent variable for region i, age group j, and income level k in month t. We use the EC household share (in percent) and EC spending (on a natural log scale) as separate dependent variables.

The first and second terms on the right-hand side of the equation are the intercept and the linear time trend, respectively. The third term captures the impact of changes in mobility at the regional level on online consumption, where for z_{it} we use the mobility trends for places such as restaurants, shopping centers, and theme parks, based on location data provided by Google Inc. (measured as the change from the baseline in percent, where the baseline is the level right before the start of the pandemic). As a robustness check, we alternatively use the number of confirmed new COVID-19 cases (number of persons per 10,000 population). Chart 2 plots developments in these variables for Japan overall.

Note that regarding the mobility trends, we set $z_{it} = 0$ for the period before March 2020. We do the same for the number of confirmed new cases before January 2020. The fourth term represents the change in online consumption after the outbreak of the pandemic, since s_t takes zero before March 2020 and one after April 2020. The fifth term, $\boldsymbol{d}_{jkt}$, is a vector of the following dummy variables: a month dummy to control for seasonality, an age group dummy, and a dummy for households' annual income level. The vector of the corresponding coefficients, $\boldsymbol{\gamma}$, quantifies the impact of seasonality and household characteristics on the EC household share and EC spending.

In the regression, if coefficient b on variable s_t is positive and significant after controlling for seasonality, household characteristics, and the COVID-19 situation (as measured by the impact on mobility or the number of new infections), this suggests that online consumption has shifted upward since the outbreak of COVID-19. In this case, online consumption is likely to remain at the higher level even when the effect of COVID-19 wanes and z_{it} returns to zero. In addition, this estimation framework gauges the contribution of each explanatory variables to changes in the EC household share and EC spending.

In terms of age, the dataset divides households into those with a household head under 35 years old, 35–39 years old, 40–44 years old, and so on in 5-years intervals, up to 80–84 years old, and 85 years old and over. Because the number of observations for those aged 80 and over is quite small, we drop these groups in our analysis. In the estimation, we define the following five age groups: those in their (i) 30s and younger (aged up to 39), (ii) 40s (40–49 years old), (iii) 50s (50–59 years old), (iv) 60s (60–69 years old), and (v) 70s (70–79 years old). Further, we assume that the coefficients for households in a particular age group are identical. Similarly, in terms of income, the dataset divides households into those receiving less than 1 million yen a year, those receiving 1 to 2 million yen, etc., in 1 million yen intervals, up to those receiving 9 million yen or more but less than 10 million yen, followed by those receiving 10 million or more but less than 12.5 million yen, 12.5 million yen or more but less than 15 million yen, 15 million yen or more but less than 20 million yen, and those receiving 20 million yen or more. For the estimation, we define the following six income level groups: (i) less than 2 million yen, (ii) 2–4 million yen, (iii) 4–6 million yen, (iv) 6–8 million yen, (v) 8–10 million yen, and (vi) 10 million yen and over. Again, we assume that the coefficients for households in a particular income group are identical. Later, we introduce dummy variables for the region in which a household resides. The dataset identifies nine regions across Japan: Hokkaido, Tohoku, Kanto, Hokuriku, Tokai, Kinki, Chugoku, Shikoku, and Kyushu-Okinawa.

The estimation period is from January 2015 to December 2020, which is the period for which we ordered the tailor-made statistics based on the HE Survey. The number of observations is 1,260 for each month, and the total number of observations is 90,720. We use ordinary least squares for the estimation.

2.4. Baseline estimation result

Chart 3 reports the results of this baseline estimation. In Model I, the coefficient on the mobility variable is negative and statistically significant at the 1% level. The coefficient estimate is −0.16, which indicates that the EC household share increases by 1.6 percentage points when mobility drops by 10% relative to the baseline (before the pandemic). This result suggests that the increase in online consumption is partly due to households refraining from going out during the pandemic. Next, when using EC spending as the dependent variable, the coefficient on the mobility variable is −0.011 and again statistically significant (Model III). This result suggests that EC spending increases by 11% when mobility decreases by 10%. We check the robustness of these result by replacing the mobility variable by the number of new confirmed cases of COVID-19 in Models II and IV. The estimated coefficients are both statistically significant and indicate that an increase in the number of cases is associated with an increase in the EC household share and EC spending.

Coefficient b on variable s_t, which measures the upward shift in online consumption during the pandemic is positive and significant in all specifications (Models I–IV). The estimates indicate that the EC household share has increased by 1–2 percentage points and EC spending has increased by 10–20% since April 2020 due to the pandemic once the various other variables are controlled for. The statistically significant coefficient implies that the increase in online consumption is likely to be highly persistent even when the impact of the pandemic wanes.

One caveat in this analysis is that the observation period for the period since the outbreak of COVID-19 is quite short and only goes up to December 2020. The pandemic has continued in 2021 as well as going into 2022, and we therefore need to update the data, which we are hoping to do in the future.

2.5. Estimation results for household groups

Next, using the following regression, we investigate which household groups increased their online consumption:

$$y_{ijkt} = c + q \cdot t + \boldsymbol{g}_0 \cdot \boldsymbol{D}_{ijkt} + \boldsymbol{g}_1 \cdot \boldsymbol{D}_{ijkt} \cdot s_t + \boldsymbol{\gamma} \cdot \widetilde{\boldsymbol{d}}_{ijkt} + \varepsilon_{ijkt}.$$

In the third and fourth terms on the right-hand side of the equation, $\boldsymbol{D}_{ijkt}$ is a vector of one set of the dummy variables (groups by age, annual income level, and regions), and $\widetilde{\boldsymbol{d}}_{ijkt}$ in the fifth term is a vector consisting of the remaining dummy variables including the month dummies for seasonality. The third term captures the increase in the EC household share of household group $\boldsymbol{D}_{ijkt}$, while the fourth term quantifies the changes in the behavior of household group $\boldsymbol{D}_{ijkt}$ during the pandemic, since the coefficient $\boldsymbol{g}_1$ measures the marginal deviation from the sample mean and the linear trend in the EC household share or in EC spending of each household group.

Chart 4 plots estimates of coefficient $\boldsymbol{g}_1$ for each age group, with the vertical lines representing the 95% confidence intervals. The estimates indicate that the EC household share increased in a wide range of age groups. The increase was largest among those in their 40s. Such households are likely to have children who were forced to stay at home when schools were closed due to the pandemic, and parents may have spent more time at home than before the pandemic, which may have led to the increase in online consumption. On the other hand, the increase among households in their 70s is not statistically significant. This result indicates that among such households the EC household share did not increase during the pandemic.

Regarding the impact on EC spending, the coefficients for all age groups are positive and statistically significant, indicating that during the pandemic the average online spending per EC household rose above the pre-pandemic trend. In addition, the results suggest that the increase was more pronounced the younger the household, although the average EC expenditure of households in their 70s also increased.

Next, we estimate the pattern in online consumption by annual income level. The results are reported in Chart 5. They indicate that both the EC household share and EC spending increased among a wide range of households, with the exception being the EC household share among households with an annual income of less than 2 million yen. The results also highlight some heterogeneity across income groups. The EC household share has increased more among households with relatively high annual incomes. Furthermore, EC spending has risen more among households with an annual income of 8–10 million yen and over 10 million yen than other households. A reason for this heterogeneity may be that households with a high annual income level are more likely to be able to afford paying the entry costs and purchasing products online without seeing or trying them before purchase.

Lastly, we run the regression using the dummies for the region in which households reside for $\boldsymbol{D}_{ijkt}$. The results are shown in Chart 6 and indicate that the EC household share increased in all regions of Japan. The estimates are statistically significant except for Hokkaido and Shikoku. In addition, the coefficients for EC spending are all positive and statistically significant. It is interesting to note that online consumption increased almost uniformly across Japan despite the heterogeneity in the spread of COVID-19 across regions. This household behavior may reflect firms' increased investment in e-commerce during the spread of COVID-19.

In sum, the analysis using the granular tailor-made statistics of the HE Survey suggests that the share of households that make online purchases has increased and that, moreover, the average expenditure per such household has grown among a wide range of households in terms of age groups, annual income levels, and regions. The estimation results suggest that online consumption activities may have taken deeper roots among households than before. In the next section, we investigate whether this result is robust using a completely different dataset, namely, the transaction data provided by Money Forward, Inc.

3. Analysis using the dataset provided by Money Forward, Inc.

3.1. Data

The MF dataset is based on the transaction data of individuals using "Money Forward ME." Money Forward ME is the online personal finance management service provided by Money Forward, Inc. and is available through its website and smartphone app. In our analysis, we focus on users (i) who remained registered for at least two years, (ii) who linked at least two bank accounts to the service (excluding corporate account users), and (iii) whose monthly expenditure and income do not exceed 10 million yen.[3] Based on these sample selection criteria, we construct a dataset consisting of the monthly averages of total expenditure and the amount of online purchases by age group. The sample size is about 350,000 users, which is much larger than that of the HE Survey.

The amount of online purchases is calculated based on (i) records of purchases on major e-commerce platforms whose accounts can be linked to Money Forward ME and which are therefore itemized on users' Money Forward ME accounts, and (ii) records of online purchases in credit card statements for credit cards linked to users' Money Forward ME accounts.[4] It should be noted that the data do not include spending on websites related to the purchase of services such as travel reservations and concert ticket sales. Therefore, as in the analysis using the HE Survey, we focus only on online purchases of goods.

Since the dataset is limited to users of Money Forward ME, it can be regarded as biased toward individuals with relatively high IT literacy who manage their household budgets using a smartphone or computer. In fact, the share of young people in the dataset is higher than in the population overall. In addition, the share of users in their 60s and 70s is relatively small. Therefore, it is necessary to carefully examine to what extent the estimation results

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[3] We set these sample selection rules in order to (i) compare users' consumption behavior before and after the outbreak of COVID-19, (ii) focus on users who treat "Money Forward ME" as one of their main tools for personal finance management, and (iii) exclude outliers.

[4] For example, users can link their accounts at certain major e-commerce platforms directly to their Money Forward ME account, and purchases on such platforms will be shown in users' Money Forward ME account. On the other hand, purchases at other online platforms/retailers not directly linked to Money Forward ME accounts are billed to users' credit card, and we use those credit card statements to obtain information on such online spending.

can be regarded as representative for the population overall.

3.2. Developments in the EC share

Chart 7(a) shows developments in the EC share by age group based on the MF data. Note that, as above, the EC share is the amount of online purchases divided by total spending. Among all age groups, the EC share rose moderately from 2016 to the beginning of 2020, i.e., before the outbreak of the pandemic. The share jumped sharply in April and May 2020, when the outbreak of COVID-19 in Japan became severe. Although the share subsequently declined temporarily, most recently it has followed an upward trend again. The chart further shows that the younger the age group, the higher is the EC share, and the larger is the jump in the share following the outbreak of the pandemic. Although omitted in this chart, the EC shares of those in their 30s and 50s also fit into this pattern: the series lie between those in their 20s and 40s and between those in their 40s and 60s to 70s, respectively. Because, as mentioned, the EC share cannot be calculated using numbers in the HE Survey, an advantage of the MF data is that both households' total expenditure and their EC expenditure are available, so that we can compute the EC share.

To check whether the EC share calculated from the MF data is representative for Japan as a whole, we compare the EC share to other official statistics. We calculate the EC share for all age groups by taking the weighted average of the EC shares by age group based on the MF data using the population shares of the age groups in the HE Survey as weights. Chart 7(b) plots the EC share for all age groups thus obtained. The chart shows that the EC share increased from about 2% in 2016 to about 3% at the beginning of 2020 and has risen further to a level above 4% since the outbreak of the pandemic.

We compare the EC share based on the MF data with the one partially based on the HE Survey.[5] For total expenditure, which is not available in the HE Survey, we instead use data from the *Family Income and Expenditure Survey* (FIES) by the Ministry of Internal Affairs and Communications. Therefore, it should be noted that since the numerator and the denominator used for calculating the EC share based on the HE Survey/FIES data are from different sources and therefore are not fully consistent, the results should be interpreted with some caution. Nevertheless, as shown in Chart 7(b), the EC share based on the MF data and that based on the HE Survey/FIES data are very similar. Specifically, both the level of and trend in the two shares are very similar, and both shares show an upward jump of about 1

[5] As in Section 2.1, we subtract "accommodation charges, fares, package travel expenses" and "tickets" from "total spending using the Internet" to obtain EC spending.

percentage point at the start of the pandemic.

Moreover, as also shown in Chart 7(b), the level of the EC share based on the MF data is also very close to the roughly 3% calculated from the *National Survey of Family Income and Expenditure* by the Ministry of Internal Affairs and Communications, which is conducted every five years.

This comparison of the EC share based on the MF data with the shares calculated from official statistics suggests that the MF data-based share can be regarded as representative of developments in Japan overall. Nevertheless, some caveats are in order. For instance, while we assume that the consumption activities of those in their 60s and 70s in our sample are representative of the actual online consumption trends of the elderly, this assumption should be treated with caution since the use of personal finance management applications among the elderly is generally less common than among younger generations.

3.3. Trend change in the EC share

To investigate whether the trend in the EC share has changed during the pandemic, we conduct the following regression:

$$Y_t = c + q \cdot t + \boldsymbol{\theta} \cdot \boldsymbol{h}_t + e_t,$$

where Y_t is the EC share in percent. The second term on the right-hand side of the equation is the linear time trend, while $\boldsymbol{h}_t$ in the third term is a vector of month dummies for seasonality. We estimate this regression using the data from January 2016 to March 2020. Using the estimated coefficients, we then extrapolate the pre-pandemic trend including seasonality for the months from April to December 2020 to obtain the Y_t that would have been expected in the absence of the pandemic. Chart 8 shows the actual trend in the EC share, the expected share based on the trend before the pandemic, and the deviation from the trend (i.e., e_t in the regression equation above) for all age groups together and for individual age groups. The bar plots indicate the deviation of the EC ratio from the pre-pandemic trend, i.e., the estimate of e_t.

For all age groups together, the deviation from the pre-pandemic trend appears to be about 1 percentage point following the outbreak of COVID-19. The deviation is largest for those in their 20s, exceeding 3 percentage points in April–May 2020 and remaining at around 2 percentage points in the second half of 2020. Further, the older the age group, the smaller is the deviation, and for those in their 60s and 70s it is only about 1 percentage point.

We regress the deviation on a constant and time dummies for April and May 2020, using data from April to December 2020. The dummies are included to control for the impact of the state of emergency announced by the government in response to COVID-19 for those months. Chart 9 shows the estimates of the constant in the regression. The chart indicates that the younger the age group, the larger is the estimate, indicating that younger individuals increased their online consumption more during the pandemic than older individuals, with those in their 60s and 70s increasing their online consumption by 0.5 percentage points. The estimate for all age groups together is about 1 percentage point. This result implies that the increase in online consumption since the outbreak of COVID-19 has had a noticeable impact on overall goods purchases in Japan, the annual amount of which was about 120 trillion yen before the pandemic.

3.4. Transitions of EC users

We explore whether EC users in the MF data who started making online purchases due to the pandemic have continued making online purchases throughout by examining the transition of individuals between being EC users (making online purchases) and non-EC users (not making online purchases). Specifically, we define EC users as those who make an online purchase at least once during a specific period and non-EC users as those who do not. For this analysis, we obtained aggregated data from Money Forward, Inc., so that individual users' personal information remained protected.

In our analysis, we focus on those who were non-EC users from September 2019 to February 2020, before the pandemic, and then became EC users in March–April 2020, at the start of the pandemic. As shown in Chart 10, we find that 81% of these individuals remained EC users from May to October 2020. Furthermore, 84% of these individuals remained EC users from November 2020 to April 2021.

This finding suggests that many of those who started making purchases online due to the pandemic continued to make online purchases. Two possible reasons for this result are that those who started making online purchases paid the costs associated with switching to online purchases, such as buying and learning how to use devices and setting up online accounts, and that they discovered the convenience of doing so (see Watanabe and Omori (2021) on this point). Given the results in this and the previous sections, it is likely that the increase in online consumption in Japan due to COVID-19 is likely to be highly persistent.

4. Implications for the post-pandemic period

In this section, based on the empirical results in the previous sections, we consider likely developments in online consumption in the post-pandemic period and their impact on Japan's economy. We do not cover all the impacts of the trend toward online consumption and instead focus on the impact on business fixed investment and consumer prices, which are of particular interest to governments, central banks, and academics.

4.1. International comparison of EC shares

We start by comparing the EC share in Japan with those in other countries and consider whether there is room for further increases in online consumption in Japan. Chart 11(a) shows that the EC share in 2019 was only about 3% in Japan, while it exceeded 10% in the United States and Germany. Thus, before the outbreak of COVID-19, the share of online consumption in these two countries was considerably larger than that in Japan. The chart also shows that the EC shares in the United States and Germany jumped by about 3 to 4 percentage points from 2019 to 2020, while the increase in Japan was just 1 percentage point. Next, Chart 11(b) shows the time series trends in the EC share in the United States and Japan. The EC share in the United States reached Japan's 2020 level as early as around 2010, and the pace of increase has been accelerating since then. As a result, the difference in the EC share between Japan and the United States has widened further in recent years.

Of course, the difference in the increase in the EC share due to the pandemic likely reflects differences in the pandemic situation between the countries. Moreover, the extent to which households prefer to make purchases online partly depends on national lifestyles and cultures. Therefore, although the difference in EC shares may to some extent simply reflect different circumstances and preferences, it nevertheless appears that Japan is behind the United States and other countries in the adoption of online consumption and that consequently there is considerable potential for an increase in the future.[6]

4.2. Impact on business fixed investment

The increase in online consumption is likely to have both positive and negative impacts on business fixed investment. One positive impact is that increases in online shopping are likely to boost investment in warehouses. Chart 12(a) plots the floor space of warehouse construction starts, which has been growing at a much faster pace since the start of the pandemic, partly due to the increase in online shopping. According to the Bank of Japan (2021), online retailers have built and expanded their logistics facilities in and around large

[6] Yagi *et al.* (2022) discuss the expansion of remote working amid the spread of COVID-19 and their impact on labor productivity in relation to the expansion of online consumption in Japan.

cities in response to the strong demand for online shopping during the pandemic. Meanwhile, the vacancy rate of logistics facilities has been on a downward trend in recent years and has reached quite a low level, as shown in Chart 12(b). The chart also shows the rent for logistics facilities, which has been increasing. These developments imply that logistics facilities have been attractive investment projects.

Selling goods online also requires investment in software and computer systems. Chart 12(c) shows that software investment in the retail industry has increased substantially in recent years and considerably faster than in other industries. This suggests that investment in related fields such as distribution systems has also increased significantly. To sell goods online, retailers need to invest in warehouses, distribution systems, software, and computer systems; therefore, as demand for online shopping increases, this is likely to boost investment in tangible and intangible assets in Japan.

On the other hand, if sales at offline retail stores fall due to the increase in online shopping, this may result in a decline in investment at offline stores. So far, the weakness in investment by offline stores since the start of the pandemic is likely due to temporary factors such as the decrease in mobility. However, it is important to carefully monitor whether such weakness in investment could become structural in the post-pandemic era due to the increase in online shopping.

4.3. Impact on consumer prices

Although there are some studies that have provided empirical analyses on the impact of the increase of online shopping on consumer prices, it appears that there is still too little evidence to draw concrete general conclusions. Here, we provide an overview of previous research, focusing on two perspectives: the impact on the price level and the inflation rate, and the impact on the frequency of price adjustments.

4.3.1. Effect on the price level and inflation

Existing studies argue that increased online consumption leads to downward pressure on retail prices and their rate of change. The reason can be found in the following differences between online and offline retail: (i) online retailers have lower sales costs because they do not need to have physical stores; (ii) it is easier for online retailers to change "price tags," so that they enjoy lower menu costs; and (iii) search costs for shoppers are lower online because it is easier to check the prices charged by other retailers for the same or similar goods. In addition, because of the relatively low cost of market entry online, the pricing power of incumbents is weaker in the online space than offline, putting downward pressure on online prices. Finally, if online retail prices are lower than offline prices, this will exert downward pressure on the price charged by offline retailers through greater competition in the market overall.

A number of studies have examined these issues empirically. For example, comparing the online retail prices of major US online retailers with the offline-store prices of large retailers in the same product category, Cavallo (2017) finds that online prices on average are about 6% lower than offline prices. Meanwhile, comparing the inflation rate of online retail prices in the United States and inflation as measured by the consumer price index (i.e., offline store prices) after adjusting for differences in product categories, Goolsbee and Klenow (2018) find that online retail price inflation is about 1.3 percentage points lower than CPI inflation. Similarly, investigating the effect of online consumption on consumer prices in Japan, Jo *et al.* (2019) obtain similar results as Cavallo (2017) and Goolsbee and Klenow (2018).

In contrast to these studies, Calligaris *et al.* (2018) argue that as online consumption grows, the online market becomes more oligopolistic, and if a few online retailers become dominant, this may make it easier for them to raise prices. Another aspect is that an increase in delivery charges could lead to an increase in online retail prices inclusive of delivery charges. In fact, the number of parcel deliveries in Japan has grown markedly in recent years, but so has the price of parcel delivery services as measured by the Services Producer Price Index (SPPI), as shown in Chart 13(a).

4.3.2. Effect on the frequency of price adjustments

As mentioned, it is easier for online retailers to change "price tags" than for offline retailers. Some studies therefore argue that, as a result, online prices are adjusted more frequently than offline prices. For example, estimating the frequency of online and offline retail price adjustments in the United States and the United Kingdom, Gorodnichenko *et al.* (2018) show that online retail prices are revised more frequently. As online consumption expands and the frequency of price adjustments increases across the market, the elasticity of prices in response to changes in demand is likely to increase. However, to date, no empirical research on the frequency of online price adjustments in Japan has been conducted.

Conventional studies on the frequency of offline price adjustments in Japan exploit the item-specific and city-specific data of the *Retail Price Survey*, on which the Consumer Price Index is based. Using these data, Higo and Saita (2007) examine changes in the frequency of price adjustments and differences in the frequency of price adjustments between goods and services. Similarly, Nakamura and Steinsson (2007) employ a similar, disaggregated dataset that is used to calculate the headline consumer price index in the United States. These studies estimate the frequency of price adjustments based on monthly price series for individual items. If they find that prices changed from one month to another, they assume that price revisions are made once a month.

To examine and compare the frequency of price adjustments online and in physical retail stores in Japan, we focus on home appliances and proceed as follows. First, following Higo and Saita (2007), we estimate the frequency of offline price adjustments for "TV sets," "cameras and video cameras," "vacuum cleaners and washing machines," and "personal computers (PCs)" based on the *Retail Price Survey* for the period between January 2000 and July 2021. The results are shown in Chart 13(b) and indicate that the prices of "cameras and video cameras" are adjusted 0.70 times a month, while the prices of "personal computers" are adjusted 0.92 times a month.

Next, we estimate the frequency of online price adjustments using a dataset from "Price Search," a pricing survey service provided by Ierae Security Inc. The prices are collected from the websites of major online retailers in Japan every six hours. We calculate the frequency of price adjustments by assuming that the price of a particular product changes every six hours if we find the price changed compared to six hours earlier. The observation period is from November 2020 to July 2021. We compute the average of the frequencies of price adjustments for each website and item in the sample. Chart 13(b) shows the estimated frequency of price adjustments on a monthly basis. We find that the prices of "cameras and video cameras" are adjusted 5.1 times a month and those of "personal computers" are adjusted 8.3 times a month. Thus, the frequency of price adjustments online for these items is considerably higher than that offline. Similarly, for "TV sets" and "vacuum cleaners and washing machines" online price adjustments are also much more frequent.

One caveat in this analysis is that due to data constraints the estimation period for online price adjustments is short. In addition, since the survey consists of monthly data, it is not possible to accurately estimate the frequency of price adjustments for goods and services whose prices are revised more than once a month. Given that home appliance mass retailers in Japan these days use electronic price tags, it is very likely that offline stores, too, adjust prices at least once a month for some home appliances. In fact, the estimated price adjustment frequency for "personal computers" in offline stores is 0.92 times per month, which is close to 1. Based on these considerations, in future work we hope to use high-frequency granular alternative data in order to further examine the impact of the increase in online consumption on consumer prices.[7]

5. Concluding remarks

In this paper, we empirically examined developments in online consumption in Japan, focusing on changes that occurred during the COVID-19 pandemic. Because of the limited availability of data in conventional statistics that would make it possible to gauge trends in online consumption, we used granular tailor-made statistics based on the HE Survey and a dataset consisting of aggregated transaction data from the online personal finance management service provided by Money Forward, Inc. Our empirical results indicate that online consumption has increased substantially during the pandemic and that the increase is likely to be highly persistent. A caveat regarding our analysis is that our observation period, which goes up to December 2020, is relatively limited. We further highlighted that the penetration of online consumption in Japan is still smaller than that in other countries such as the United States and Germany and that there remains much room for an expansion of online consumption in the future.

In general, unlike official statistics, alternative data such as the data used in this study are typically not based on samples collected employing proper statistical sampling methods. Consequently, when using such alternative data in economic analyses, it is often necessary to make various assumptions. This means that it is important to compare and cross-check the results with data available from official statistics and other sources. In this study, we therefore examined the likely persistence of the increase in online consumption during the pandemic using two different datasets. It is likely that more data -- and different kinds of data -- will become available in the future to allow us to further deepen our understanding of developments in online consumption in Japan.

[7] An example of previous studies using high-frequency granular alternative data is the study by Sudo *et al.* (2014), who calculate the frequency of price adjustments at offline stores in Japan using daily scanner data. According to their results, the price adjustment frequency for daily necessities is about twice a month.

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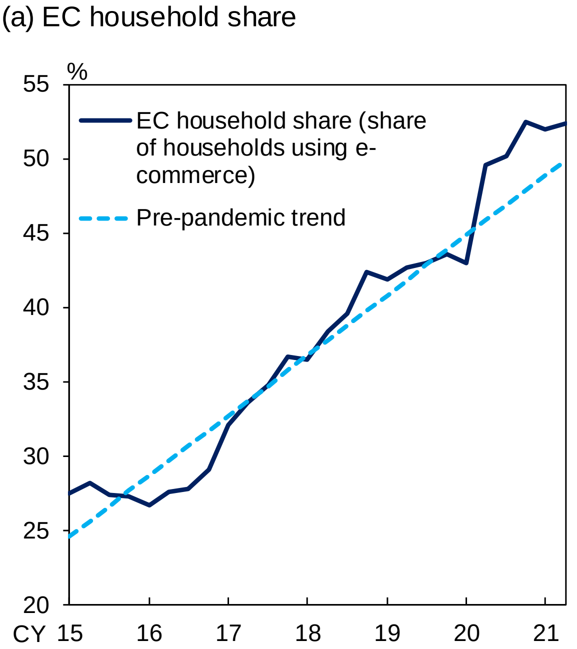
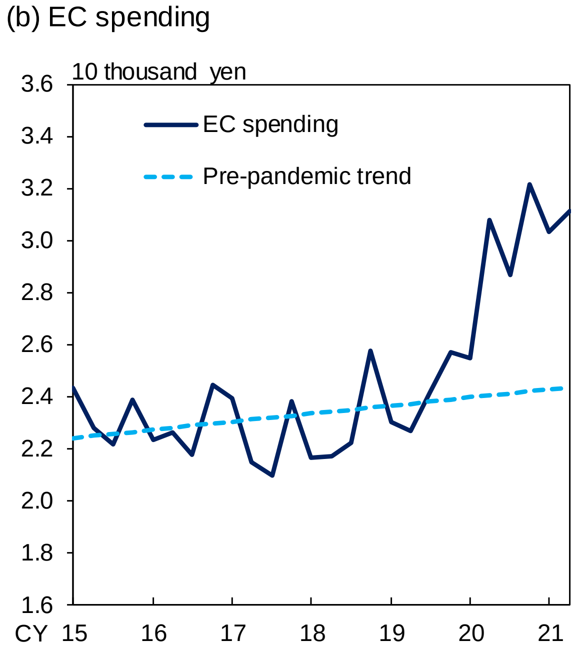
Chart 1. Online consumption in Japan: *Household Economy Survey*

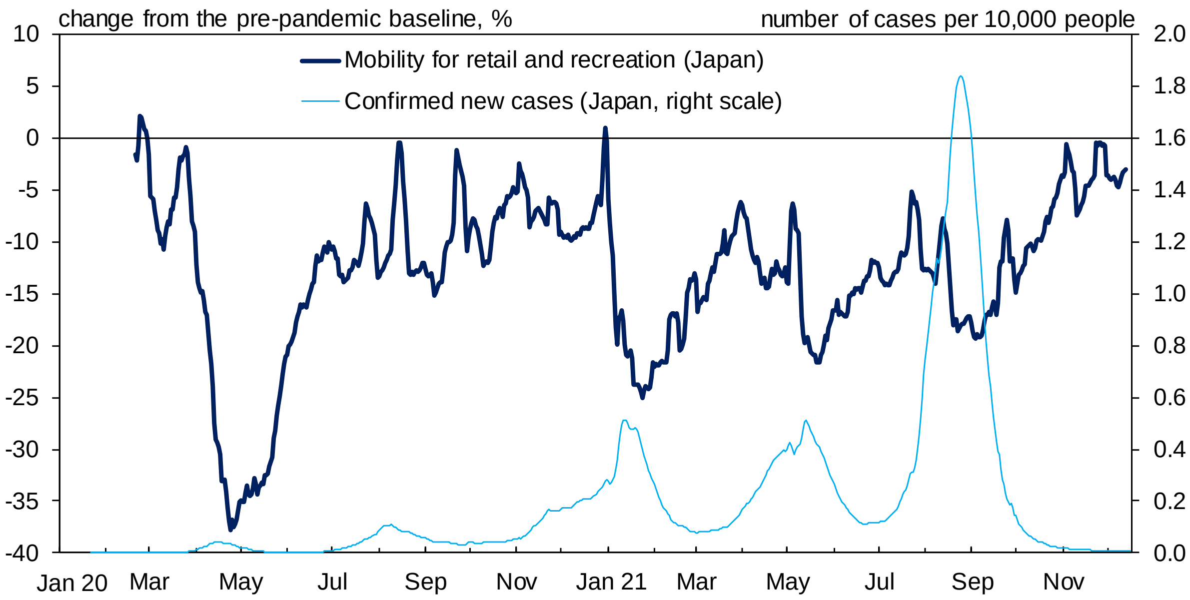




Note: The dashed lines show the linear time trend calculated from the January-March quarter in 2015 to the January-March quarter in 2020. In (b), EC spending is the spending per household of households that made purchases online. We subtract "accommodation charges, fares, package travel expenses" and "tickets" from "total spending using the Internet" to obtain EC spending.

Source: Ministry of Internal Affairs and Communications.

Chart 2. Indicators for the COVID-19 situation



Note: Figures are weekly averages. The pre-pandemic baseline for mobility is the median for the corresponding day of the week during the 5-week period from January 3 to February 6, 2020.

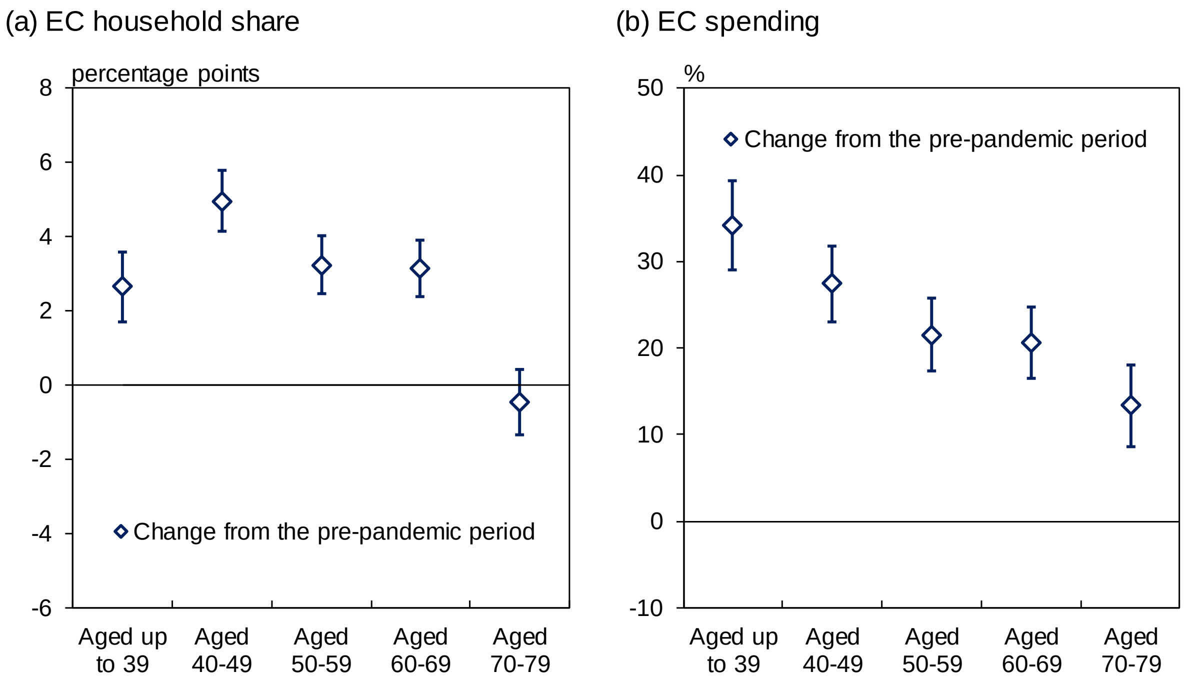
Sources: Ministry of Health, Labour and Welfare; Google.

Chart 3. Estimation result based on the HE Survey data

Dependent variable	(a) EC household share (%)		(b) EC spending (log scale)	
Model	I	II	III	IV
Mobility	-0.16 ** (0.02)		-0.011 ** (0.001)	
New COVID-19 cases		0.42 ** (0.08)		0.019 ** (0.004)
Dummy for the period from April 2020	1.12 ** (0.30)	2.15 ** (0.26)	0.118 ** (0.016)	0.200 ** (0.014)
Age group dummies	Yes	Yes	Yes	Yes
Income group dummies	Yes	Yes	Yes	Yes
Adjusted R-squared	0.593	0.593	0.108	0.107

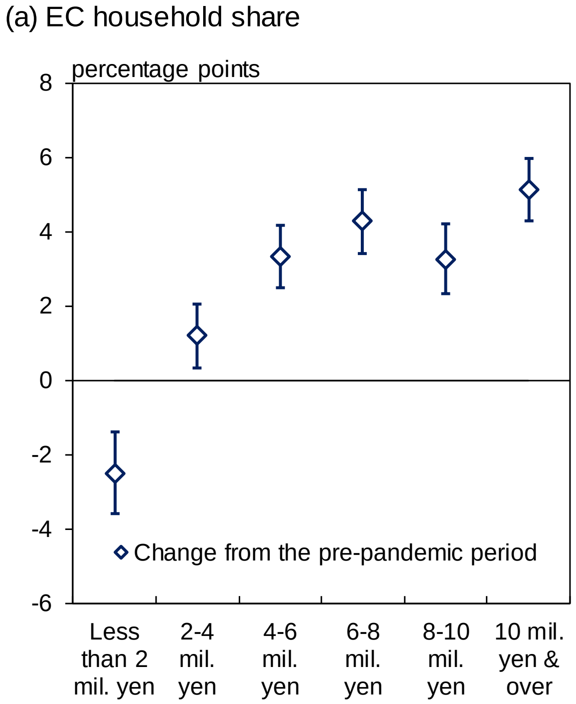
Note: Standard errors are in parentheses. ** denotes statistical significance at the 1% level. The observation period is from January 2015 to December 2020. For (b), EC spending is the spending per household of households that made purchases online.

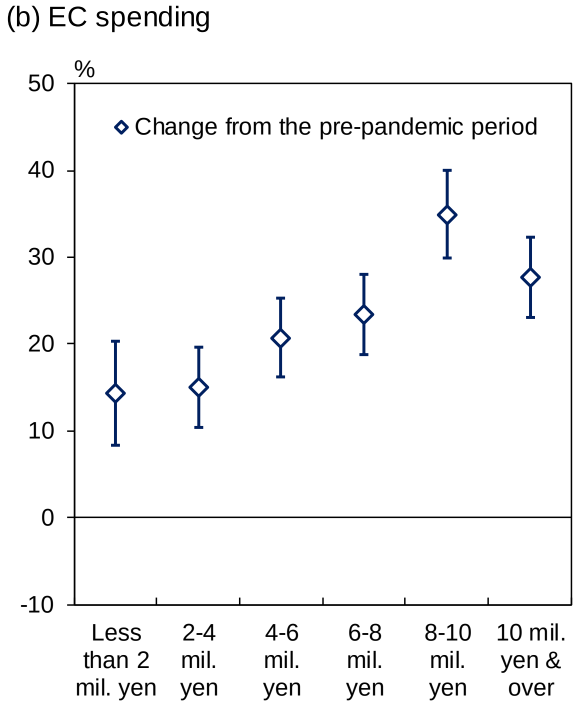
Chart 4. Estimation result based on the HE Survey data: By age group



Note: The vertical lines denote 95% confidence intervals. For (b), EC spending is the spending per household of households that made purchases online.

Chart 5. Estimation result based on the HE Survey data: By annual income level

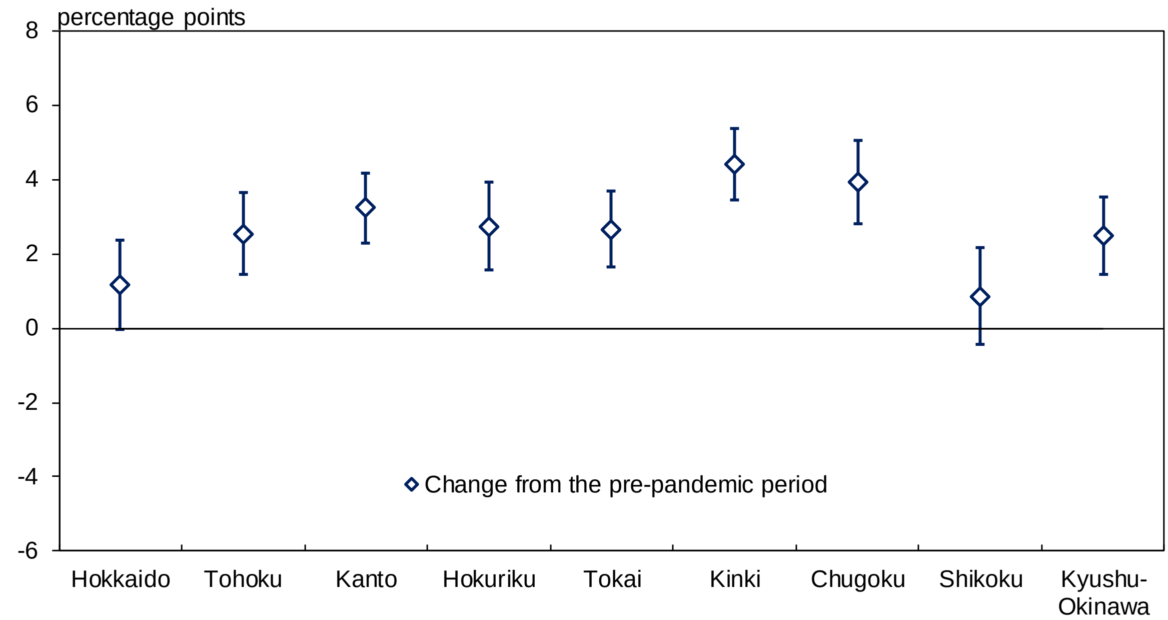




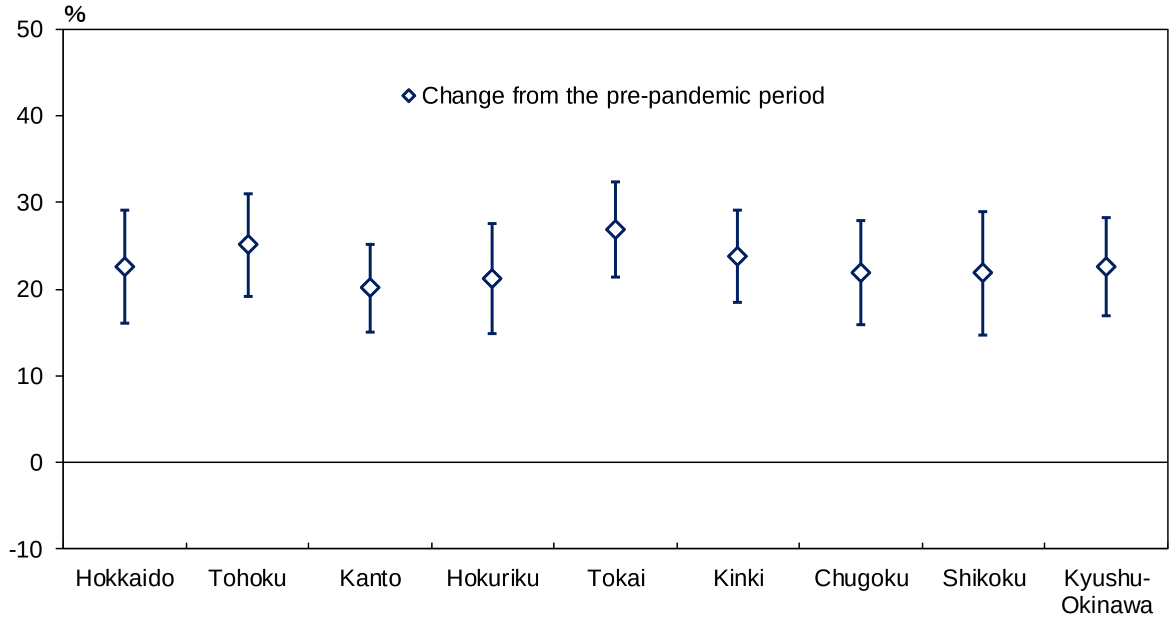
Note: The vertical lines denote 95% confidence intervals. For (b), EC spending is the spending per household of households that made purchases online.

Chart 6. Estimation result based on the HE Survey data: By region

(a) EC household share

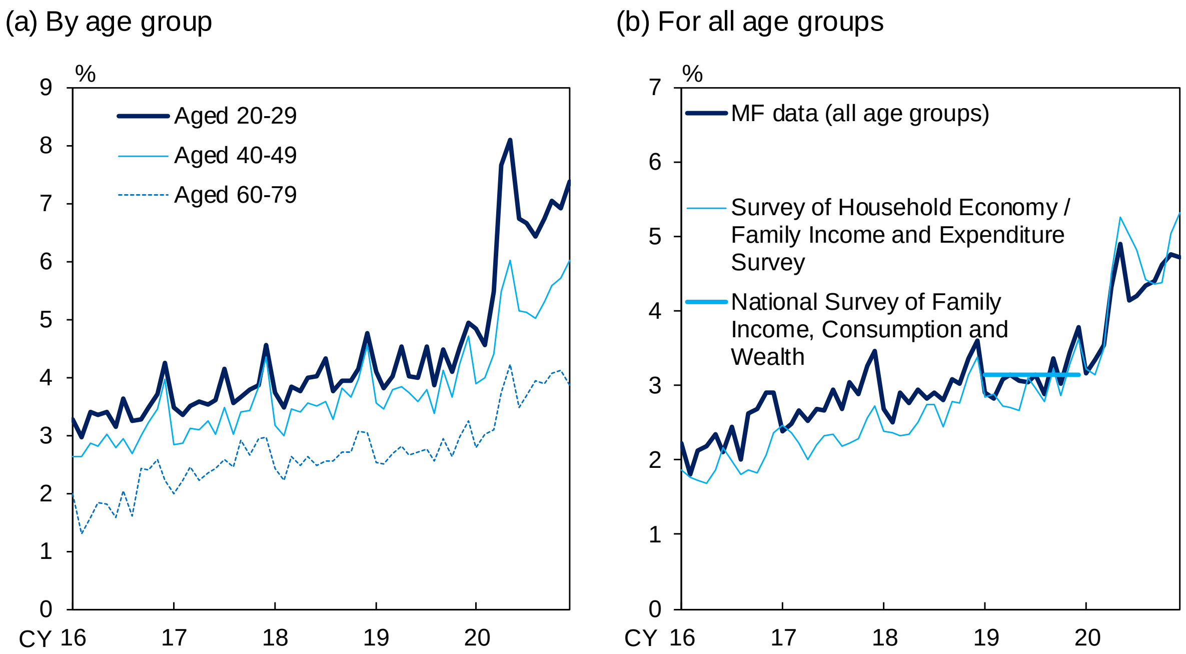


(b) EC spending



Note: The vertical lines denote 95% confidence intervals. For (b), EC spending is the spending per household of households that made purchases online.

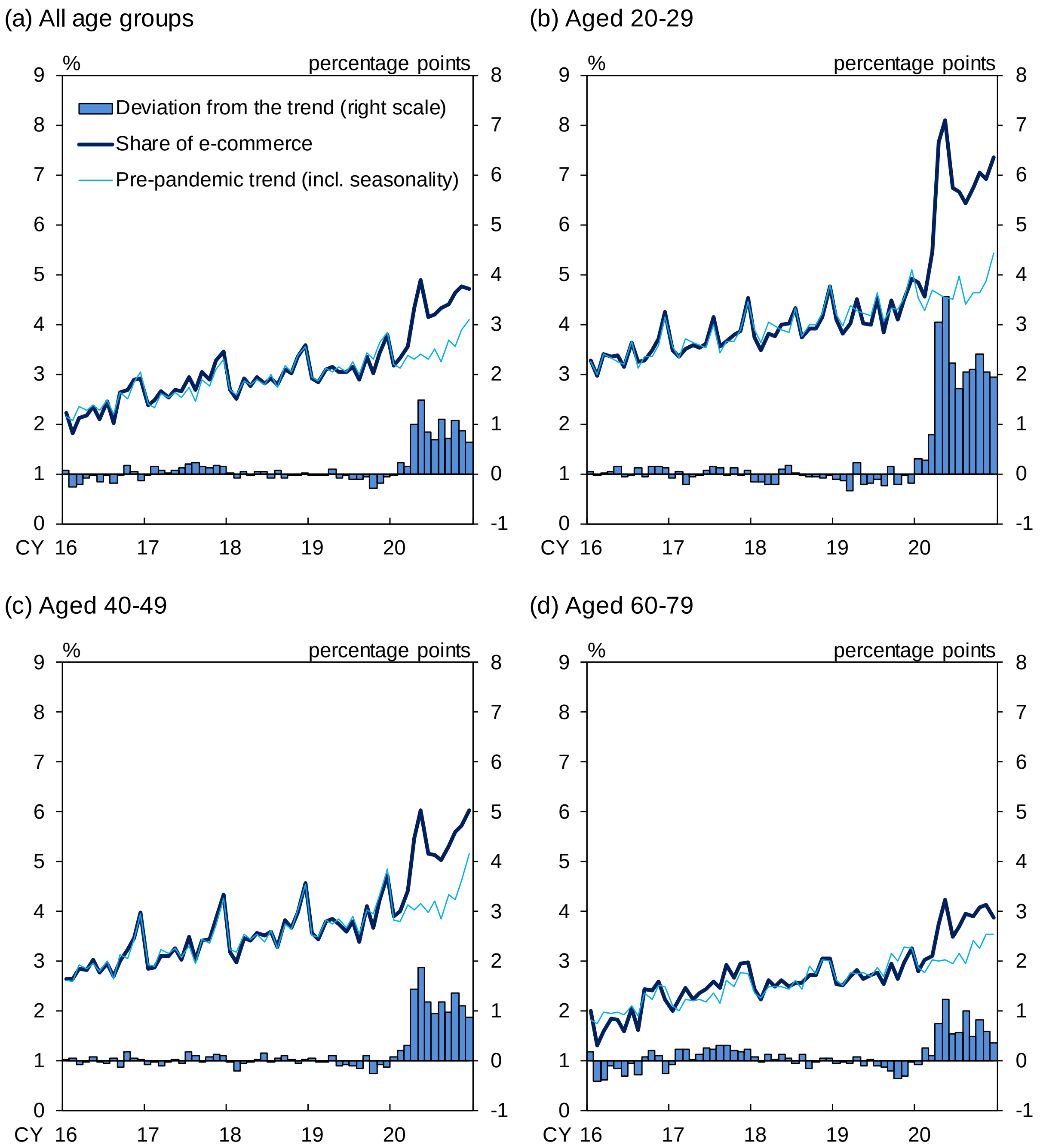
Chart 7. EC share based on the MF dataset



Note: For details on (b), see the main text.

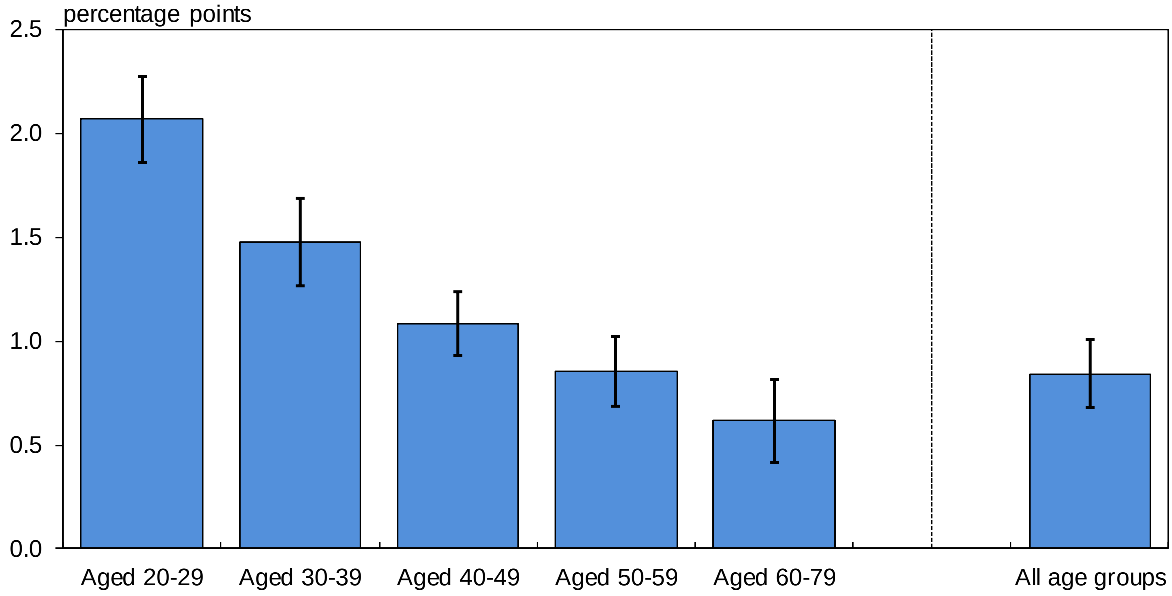
Sources: Authors' calculation based on information provided by Money Forward, Inc. and the Ministry of Internal Affairs and Communications.

Chart 8. Change in the EC share based on the MF dataset: Time series



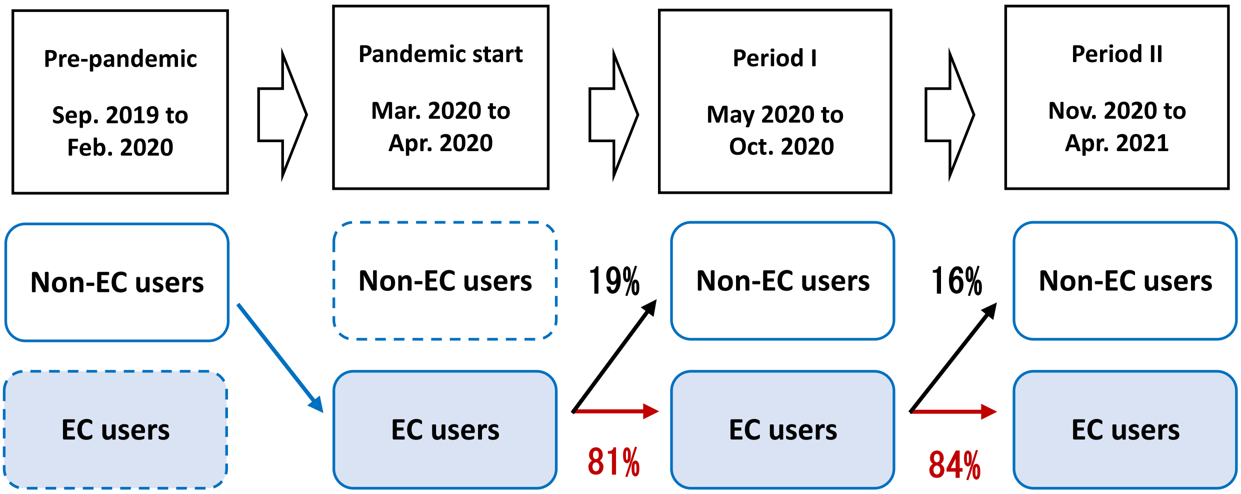
Source: Authors' calculation based on information provided by Money Forward, Inc.

Chart 9. Change in the EC share based on the MF dataset: Estimates of the change



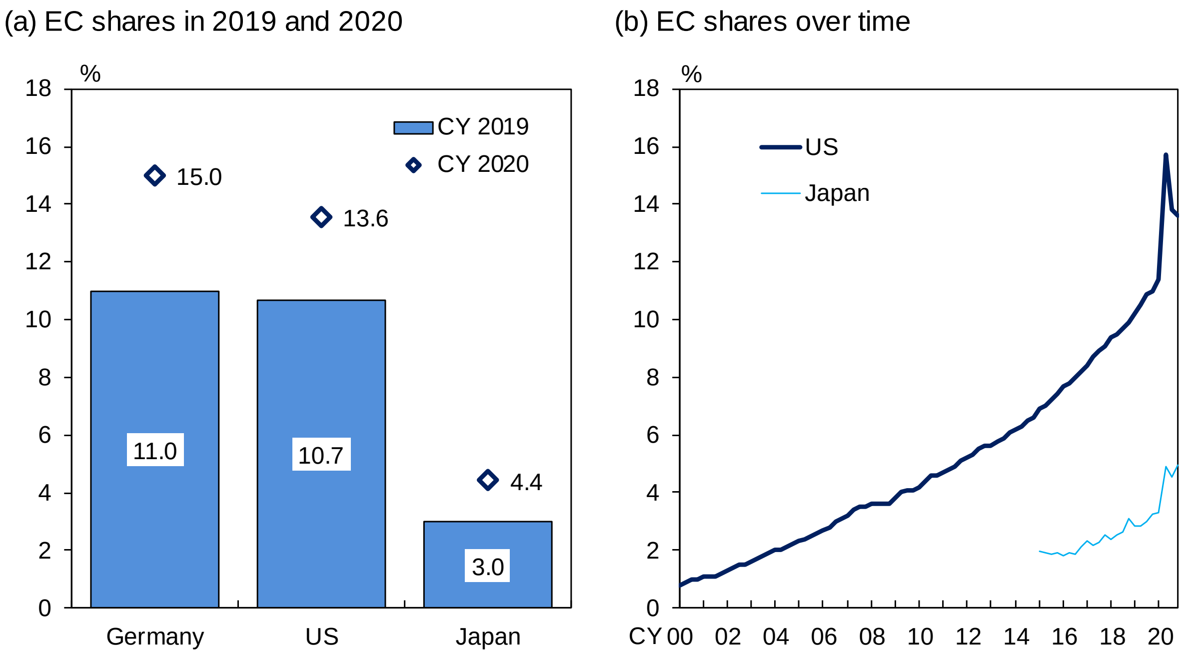
Note: The vertical lines denote 95% confidence intervals.
Source: Authors' calculation based on information provided by Money Forward, Inc.

Chart 10. Transitions of EC users in the MF dataset



Source: Authors' calculation based on information provided by Money Forward, Inc.

Chart 11. International comparison of EC shares

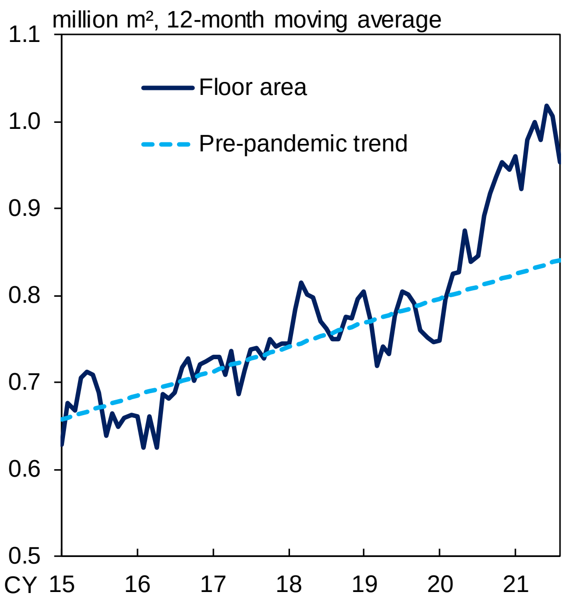


Note: For Japan, the EC share is computed by dividing the online spending obtained from the HE Survey by the total expenditure obtained from the FIES. For online spending, we exclude "accommodation charges, fares, package travel expenses" and "tickets" from "total spending using the Internet." For Germany and the United States, the EC shares are computed as the share of online sales in total retail sales. In (b), the figures for the United States are seasonally adjusted.

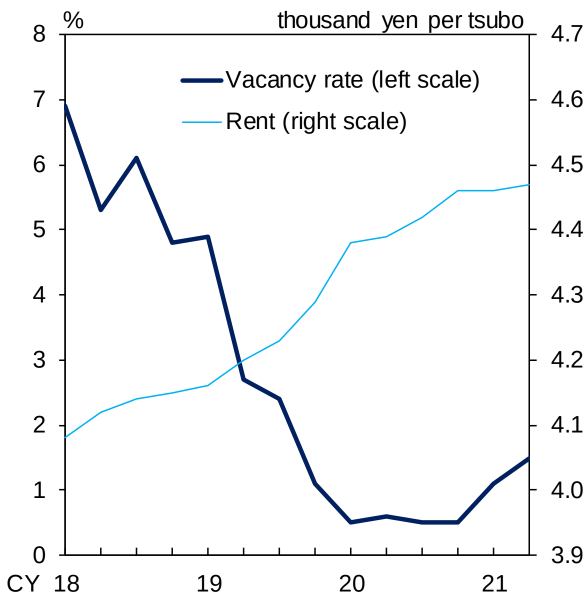
Sources: Ministry of Internal Affairs and Communications; Census Bureau; Eurostat.

Chart 12. Impact of increasing online consumption on business fixed investment

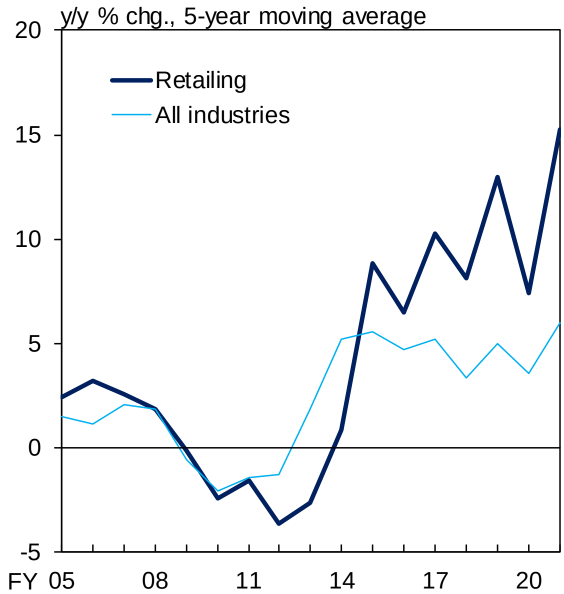
(a) Warehouse construction starts



(b) Logistics facilities (Greater Tokyo Area)

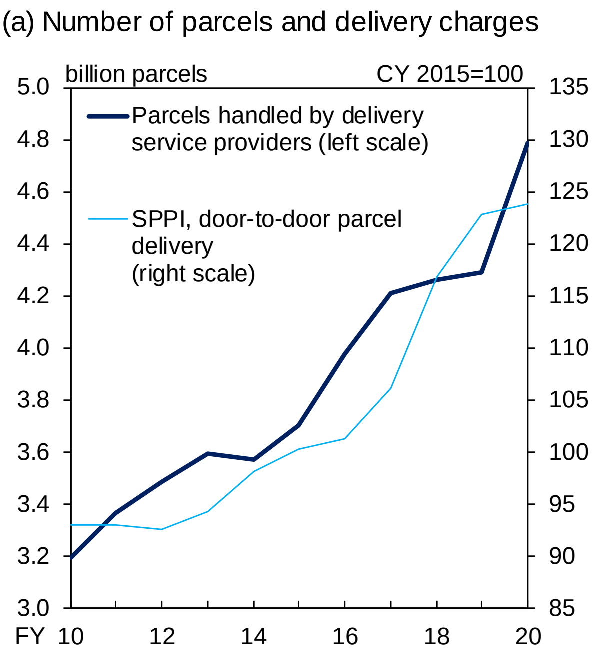


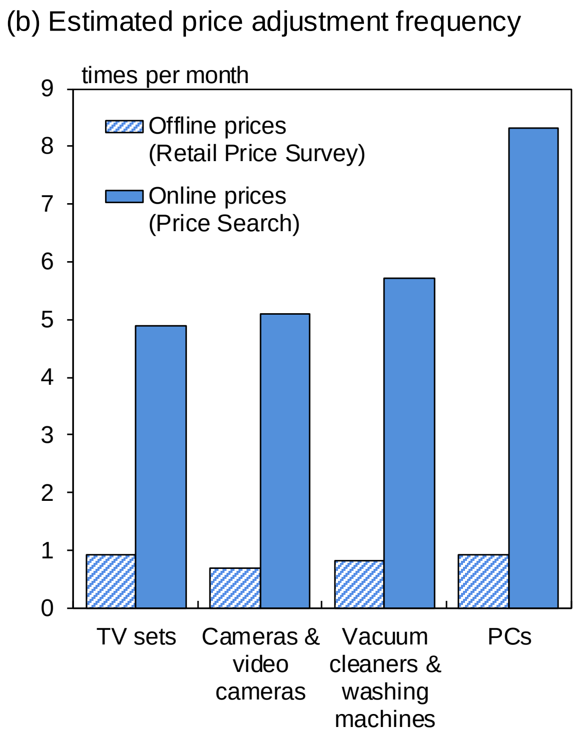
(c) Software investment



Note: In (a), the dashed line shows the linear time trend calculated from January 2015 to December 2019. In (c), the figures for 2021 are the figures for planned investment as of September 2021.
Sources: Ministry of Land, Infrastructure, Transport and Tourism; CBRE; Bank of Japan.

Chart 13. Parcel delivery charges and frequency of price adjustments





Note: In (a), the figures for the SPPI exclude the effect of the consumption tax hikes. In (b), the frequency of offline price adjustments is computed using the *Retail Price Survey* from January 2020 to July 2021. The frequency of online price adjustments is computed using the "Price Search" dataset provided by Ierae Security Inc., which consists of online price information every six hours. The observation period of the "Price Search" dataset is from November 2020 to July 2021.

Sources: Ministry of Land, Infrastructure, Transport and Tourism; Bank of Japan; Ministry of Internal Affairs and Communications; Price Search.