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Has COVID-19 Permanently Changed Online Consumption Behavior?[1]

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Abstract

This study examines how the COVID-19 pandemic has affected online consumption using data from a major online shopping platform in Japan. Our particular focus is the effect of two measures of the pandemic, i.e., the number of positive cases of COVID-19 and the declaration of states of emergency to mitigate the pandemic. We find that both measures promoted online consumption at the beginning of the pandemic, but their effect then faded in later periods. In addition, online consumption is found to have returned to normal after states of emergency ended, and the overall time trend in online consumption excluding the effects of the two measures was also stable during the first two years of the pandemic. These results suggest that the effect of the pandemic on online consumption is temporary and will not persist after the pandemic.

Keywords: Consumer behavior, Online consumption, Online shopping, COVID-19; State of emergency; Stay at home; BtoC
JEL classification: D12, H12, M31

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Introduction

The COVID-19 pandemic that started in earnest in early 2020 largely affected consumer behavior. Accordingly, a number of academic studies have examined the effect of the pandemic and associated policies on consumption from various perspectives. It is often found that consumers purchased more essential products, such as medical and health products and foods, during this period, while total consumption decreased because of a larger decline in the consumption of nonessential products (Baker *et al.* (2020); Chen *et al.* (2021); Chronopoulos *et al.* (2020); Coibion *et al.* (2020); Cruz-Cárdenas *et al.* (2021); Di Crosta *et al.* (2021); Gupta *et al.* (2021); Konishi *et al.* (2021); Morikawa (2021a); Nielsen (2022)). One possible reason for the increase in consumption of essential products was "panic buying" and hoarding because of consumers' fears that the pandemic and government restrictions would result in a shortage of supplies (Chronopoulos *et al.* (2020); Nielsen (2022); Keane & Neal (2021); Sheth (2020)), sometimes stimulated by mass media (Koch *et al.* (2020)). Similar consumer behavior has been observed during other disasters, such as Hurricane Katrina in 2005 (Sneath *et al.* (2009)) and the 2009 swine flu pandemic caused by the H1N1 influenza virus (Goodwin *et al.* (2009)).

One strand of literature particularly focuses on the effect of the COVID-19 pandemic on online shopping. Because government restrictions, including lockdowns, often require or request that people stay home and businesses close down, consumers may go shopping in person less frequently and thus should rely more on online shopping. In addition, even without any restrictions, consumers may stay home out of fear of infection. This has been confirmed by several studies based on their surveys in the United States (Jensen *et al.* (2021); Mason *et al.* (2020)), China (Gao *et al.* (2020)), and Vietnam (Tran (2021)) and by a study based on online transaction data at the country level in France (Guthrie *et al.* (2021)).

One remaining question regarding the effect of the pandemic on online shopping is whether the increase in online shopping will persist after the pandemic. In the early period of the pandemic, several authors predicted that the pandemic would lead to permanent changes in consumer behavior, including the increased usage of online shopping channels (Sheth (2020); Kim (2020)). In addition, it has been empirically found that consumers in the US plan to continue online grocery shopping after the pandemic (Jensen *et al.* (2021)) and that online shopping in Vietnam will continue while fears about the pandemic are sufficiently high (Tran (2021)).

On the one hand, these predictions are justified because participating in online shopping incurs initial costs such as setting up new accounts, learning how to use online shopping sites safely, and learning how to evaluate products online accurately (Cai & Cude (2016)). Therefore, once consumers were forced to begin online shopping by the pandemic, they became likely to continue to shop online because of the benefits of doing so, such as easier information searching and lower transportation costs (Kim (2020)).

On the other hand, the continued use of online shopping is not guaranteed because shopping in physical stores or offline shopping is still beneficial. For example, offline shopping is often motivated by the desire for immediate possession and social interactions (Kim (2020); Rohm & Swaminathan (2004)). Moreover, online shopping is useful but is also associated with certain costs. Privacy and security are at risk when shopping online. Processing online information requires greater cognitive resources than processing printed information (Cai & Cude (2016)). If the net benefit of offline shopping is greater than that of online shopping, consumers will rely on offline shopping even after paying the initial costs of online shopping. Furthermore, although consumers are often panicked and react exaggeratedly at the beginning of a large shock, they learn to cope with the new situation and react less to the shock over time (Guthrie *et al.* (2021)). The effect of the COVID-19 pandemic on fear and anxiety has also been found to diminish over time (Borbás *et al.* (2021)). Therefore, consumers who are accustomed to the pandemic may have weaker reactions to it than they did before and return to old habits in the long run (Sheth (2020)).

Empirically, whether the effect of the COVID-19 pandemic on online consumption will persist has rarely been tested in the academic literature using data covering a long period of the pandemic (Guthrie *et al.* (2021)). One exceptional study (Watanabe & Omori (2020)) used large-scale data on credit-card transactions in Japan in January and April 2019 and 2020. The study found that although the share of online shopping in total consumption increased during this period of the pandemic, the probability that nonusers of online shopping started online shopping after the pandemic began was the same as that in the pre-pandemic period. Accordingly, it was predicted that once the pandemic subsides, online consumption will return to pre-pandemic levels.

The present study revisits this question using data on the amount of purchases in a major online shopping platform in Japan from January 2019 to October 2021. Specifically, we employ two measures of pandemic shocks: the number of positive cases of COVID-19 and the declaration of a state of emergency to mitigate the pandemic. Then, we estimate the effect of each measure on online purchases on the platform using a difference-in-differences (DID) approach. Our approach is relevant because our sample period covers one year preceding the pandemic, several waves of COVID-19 cases, and several stages of states of emergency and because the level of pandemic shocks varied substantially across prefectures in Japan. In addition, we check whether the effect of the shocks diminished over time. Finally, to determine whether the effect of the shocks persisted, we examine how online purchases changed after each wave of COVID-19 cases and state of emergency and how the time trend in online purchases after excluding the direct effect of the shocks changed over time.

Data

Our data are taken from three data sources. First, we utilize daily data on the amount of purchases and the number of buyers on an online shopping platform, Yahoo! Shopping (hereafter Yahoo), licensed by the company. Yahoo is the third largest online shopping platform in Japan, following Amazon Japan and Rakuten, and its total sales in 2019 were 1,501 billion Japanese yen, or approximately 13.7 billion US$ using the average exchange rate for that year (Z Holdings (2022)) (Figure 1). The number of buyers is defined as the number of "unique users," not double-counting individuals who buy from the platform more than once in a day using the same Internet Protocol (IP) address. Our data cover the period from January 1, 2019, to October 30, 2021, and are aggregated at either the city or prefecture-product level. The blue line in Figure 2 shows the moving average of total purchases for one week to avoid fluctuations due to days of the week. Notably, there are several spikes, most likely because of sale periods.

In each observation, when the number of buyers is quite small and individual buyers thus might be identified, the amount of purchases and number of buyers are hidden due to Yahoo's privacy policy. Therefore, among 1,718 cities, wards, towns, and villages, which we broadly define as "cities," in Japan in total, our city-level data include approximately 1,100 data points each day.

Yahoo classifies products into 17 categories. Among them, the data for "gifts" and "house-keeping services" are often missing, possibly because of their small numbers, and the data for "videos and music" and "books" are mostly missing in 2019 for undisclosed reasons. Therefore, we drop these four product categories from our analysis at the prefecture-category level. We further reclassify the remaining 13 categories into four categories for simplicity, mostly depending on whether they are considered essential during the pandemic: (1) health-related products, including "health products," "health foods," and "medicine"; (2) daily essentials, including "foods" and "household products"; (3) nonessential products mostly used at home that include "sweets and alcohol," "consumer electronics," "furniture," "hand tools and car supplies," and "hobby supplies"; and (4) nonessential products mostly used outside that include "cosmetics" and "clothes." The share of each category in total purchases is presented in Figure 3. The shares of health products, health foods, and medicine; food and household products; and nonessential products used outside increased over time, while the share of nonessential products used at home decreased. SI Table 1 presents summary statistics of daily online purchases at the city level by year. The mean increased from 145 thousand yen in 2019 to 245 thousand yen in 2021.

Second, the population and the number of daily positive cases of COVID-19 in each prefecture are taken from the Statistics Bureau of Japan (Statistics Bureau of Japan (2022)) and the Ministry of Health, Labor and Welfare (Ministry of Health, Labor and Welfare (2022)), respectively. We estimate the daily population in each prefecture from the yearly population in 2015 and 2020 and the estimate for 2025, assuming a constant change rate in each five-year period. Then, we calculate the number of daily cases per 1,000 persons in each prefecture. The red line in Figure 2 indicates the one-week moving average of total daily cases in Japan. We can observe five waves of COVID-19 cases during the study period: January 22-June 9, 2020; June 10-September 24, 2020; September 25, 2020-March 2, 2021; March 3-June 21, 2021; and June 22-October 30, 2021. SI Table 2 presents summary statistics of the number of cases per 1,000 at the city level.

Finally, we also utilize the information taken from the Cabinet Secretariat of Japan (Cabinet Secretariat of Japan (2022)) on states of emergency declared at the prefecture level to reduce the spread of COVID-19. In Japan, a state of emergency is declared in a prefecture by the central government after the prefectural government submits a request to the central government. After the declaration by the central government, the prefecture government can determine the details of the restrictions within the confines of the law. However, it should be emphasized that regulations during states of emergency in Japan are less strict than those in other countries. The government can only "request" that people wear masks, stay home, work from home, and close restaurants, pubs, shops, offices, and schools but cannot force them to do so, with limited exceptions. However, because of stringent social pressure in Japan, people usually follow these requests and often stay home during a state of emergency, which was particularly true at the beginning of the pandemic. According to mobility data from mobile phones, human mobility in Tokyo declined by 50% one week after the first state of emergency was declared (Yabe *et al.* (2020)), and a survey of workers in Japan indicated that the share of workers working from home increased from 10.6% in 2017 to 35.8% in June 2020 after the pandemic began (Morikawa (2021b)). However, the decline in mobility was less significant in later stages of states of emergency (Okamoto (2021)).

In response to the first wave of COVID-19 in late March 2020, an initial state of emergency was declared in seven prefectures, mostly industrial regions, including Tokyo and Osaka, on April 7, 2020. On April 16, all 47 prefectures declared a state of emergency, and this was lifted in all prefectures by May 25, 2020. After that, a state of emergency was declared in some, not all, prefectures from January to March 2021, from late April to June 2021, and from July to September 2021. The shaded bars in Figure 2 illustrate the number of prefectures in a state of emergency on each date, and the red cells in Figure 4 indicate prefectures in a state of emergency.

In addition to states of emergency, "priority measures to prevent the spread of disease" were initiated in February 2021. These measures were less strict than states of emergency, and thus we call this circumstance a semi-state of emergency. For example, in a semi-state of emergency, restaurants and pubs are often requested not to serve alcohol after 8 pm, while in a state of emergency, they are often requested not to serve alcohol at all and to close at 8 pm (although regulations have varied across time and prefectures). In 2021, semi-states of emergency were often declared before and after a state of emergency. The orange cells in Figure 4 show prefectures in a semi-state of emergency.

Methods

Benchmark equation

Our key determinants of online purchases are two measures of pandemic shocks, i.e., the number of COVID-19 cases and the dummy (indicator) variable for a state of emergency. Conceptually, there are two major reasons why pandemic shocks affect online consumption, one psychological and the other physical, as summarized in the introduction section. First, in facing the pandemic, people feel anxiety and fear about future supplies and thus purchase more essential products. Second, because of government restrictions, consumers should stay home more than before and thus naturally rely more on online shopping. The combination of the two results in an increase in online consumption, particularly of essential products. Among the two measures, the number of cases is more related to psychological factors of the pandemic effect because its increase generates fear among consumers. A state of emergency is more related to physical restrictions that affect online consumption, i.e., staying home and closing businesses. However, the two factors cannot be clearly distinguished in the two measures because an increase in the number of cases may raise fear and thus lead consumers to stay home more. Additionally, a state of emergency restricts consumers physically but promotes fear among consumers psychologically.

To estimate the effect of the two measures on online consumption, we employ a difference-in-differences (DID) approach. In particular, because the timing of the treatment (the waves of COVID-19 cases and the stages of states of emergency) varies across time and prefectures, we start with two-way fixed-effects (TWFE) estimators that incorporate individual fixed effects and time fixed effects and assume no persistent effect of treatments (Roth *et al.* (2022)). A simple estimation equation at the city level can be given as:

$$\ln Y_{cpt} = \beta_1 \ln \mathrm{CASE}_{pt} + \beta_2 \mathrm{SoE}_{pt} + \delta_c + \delta_t + \delta_d + \epsilon_{cpt}, \tag{1}$$

where Y_{cpt} is either the total amount of purchases, the number of buyers, or the amount of purchases per buyer in city c in prefecture p on date t, CASE_{pt} is the number of COVID-19 cases per 1,000 persons in p on t, and SoE_{pt} is a dummy variable that takes a value of one if p is in a state of emergency on t and zero otherwise. Although Ys are given at the city level, we lack data on the number of cases at the city level. However, our use of prefecture-level cases is justified because consumers are more concerned about the number of cases in their prefecture as reported every day by mass media (Koch *et al.* (2020)), while information at the city level is rarely reported.

We take a natural log of the amount of purchases, the number of buyers, and purchases per buyer, and we take a log of the number of COVID-19 cases per 1,000 after adding 0.001 because otherwise, the result may be zero. Therefore, β_1 can be interpreted as the quasi-elasticity of online consumption with respect to COVID-19 cases, i.e., the percentage change in the online shopping variables due to the percentage change in the number of cases. Similarly, β_2 is the percentage change in online shopping due to the declaration of a state of emergency. We incorporate fixed effects at the city (δ_c), date (δ_t), and day-of-the-week (δ_d) levels. City fixed effects control for any unobservable time-invariant factor that affects online consumption behaviors, such as geographic and cultural factors, whereas date fixed effects represent the time trend that is common to all cities. Day-of-the-week fixed effects are included to capture fluctuations across the days in a week. We estimate Equation (1) by ordinary least squares (OLS). This estimation strategy is justified because changes in the two measures of pandemic shocks can be considered exogenous shocks to consumption behaviors. Standard errors are clustered at the city level, incorporating possible correlation between the error terms within the city across time.

Extensions

This study extends Equation (1) in three ways. First, we examine heterogeneity in the effect of COVID-19 cases and states of emergency across time, following the recent literature on DID (Roth *et al.* (2022); De Chaisemartin & d'Haultfoeuille (2020); Callaway & Sant'Anna (2021)). Because the pandemic lasted for one and a half years in the sample period, consumers may have coped with the pandemic and thus may have responded less to the pandemic shocks as time went on (Guthrie *et al.* (2021)). In the presence of heterogeneity in treatment effects across time, the coefficient of the treatment variables in Equation (1) is the weighted average of the time-varying effects and can be biased (Roth *et al.* (2022); De Chaisemartin & d'Haultfoeuille (2020); Goodman-Bacon (2021)). Therefore, we incorporate time heterogeneity in the effect of pandemic shocks by distinguishing among the number of COVID-19 cases across the five waves and among the states of emergency in different months.

Second, we include dummy variables for before and after a state of emergency. Specifically, we incorporate a dummy variable that takes a value of one if prefecture p declared a state of emergency on date $t+1$; i.e., p is one week before a state of emergency is declared, and zero otherwise. Similarly, three other dummy variables for 2–4 weeks before a state of emergency are also included. The reason for including pre-state-of-emergency dummies is to check whether a state of emergency has any effect prior to its declaration through anticipation of the declaration in the near future. Usually, a few days before the central government declares a state of emergency in a prefecture, its governor requests a declaration from the central government in response to increasing cases in the prefecture. Therefore, a state of emergency is generally predictable a few days before its actual declaration. In addition, we incorporate dummy variables for 1–4 weeks after any state of emergency. This enables us to test whether the possible effect of a state of emergency persisted even after the declaration was lifted, a major hypothesis in this study, as described in the introduction. The absence of the post-state of emergency effect is a major assumption of static TWFE estimations using equations such as (1) and thus should be tested.

Finally, we examine spillover effects, i.e., whether consumer behavior in prefecture p is affected by any COVID-19 case or state of emergency in neighboring prefectures because of fear of the spread of COVID-19 and the resulting state of emergency in p in the future. If spillover effects exist, β_1 and β_2 in Equation (1) may be biased (Miguel & Kremer (2004)). For this purpose, we include in Equation (1) the total number of cases in prefectures that share any border with prefecture p and the number of neighboring prefectures in a state of emergency. As in the previously defined variables, we distinguish among the number of cases in neighboring prefectures by wave and among the number of neighboring prefectures in a state of emergency by month.

Accordingly, our city-level analysis is based on the following equation:

$$\begin{aligned}\ln Y_{cpt} = &\sum_{w} \beta_{1w} \ln \mathrm{CASE}_{ptw} + \sum_{m} \beta_{2m} \mathrm{SoE}_{ptm} \\ &+ \sum_{y=2020}^{2021} \sum_{k=1}^{4} \lambda_{1y} \mathrm{PreSoE}_{ptyk} + \sum_{y=2020}^{2021} \sum_{k=1}^{4} \lambda_{2y} \mathrm{PostSoE}_{ptyk} \\ &+ \sum_{w} \mu_w \ln \left(\sum_{q \in Q_p} \mathrm{CASE}_{qtw} \right) + \sum_{m} \mu_m \sum_{q \in Q_p} \mathrm{SoE}_{qtm} + \delta_c + \delta_t + \delta_d + \epsilon_{cpt},\end{aligned} \tag{2}$$

where CASE_{ptw} is the number of COVID-19 cases per 1,000 persons in prefecture p on date t in wave w (w is from one to five), and SoE_{ptm} is the dummy variable that takes a value of one if p is in a state of emergency in t in month m. PreSoE_{ptyk} and $\mathrm{PostSoE}_{ptyk}$ are one if p is k in the weeks before and after a state of emergency, respectively, in t in year y and zero otherwise. Q_p is the set of prefectures that neighbor p. semi-states of emergency, which are less restrictive than states of emergency (refer to the previous section), are also included in the analysis but are not distinguished according to month of declaration for simplicity.

There are several remaining econometric issues in estimating Equation (2). First, from April 16 to May 14, 2020, all 47 prefectures in Japan were in a state of emergency. Because we cannot compare prefectures with and without a state of emergency during this period, we drop it from the sample (Roth *et al.* (2022)).

Second, when the timing of treatments varies, the estimate of the treatment variables without any consideration of the time variation may be biased. We alleviate this problem by incorporating the time-variant effects of the COVID-19 shocks, as explained earlier. Moreover, this bias may be minimal in this study because prefectures that declared a state of emergency earlier than others lifted it later than others in all three stages (Figure 4). Therefore, our estimation avoids biases arising from comparison among prefectures that were in a state of emergency but are currently not and prefectures that are currently in a state of emergency, assuming that the former would not have been treated (Goodman-Bacon (2021)).

Finally, an important identifying assumption of DID estimations is a parallel trend prior to the treatment. If there is any difference in the pre-pandemic trend between prefectures that were severely hit by COVID-19 and thus declared a state of emergency for a long time and other prefectures, βs in Equation (2) may not simply be the effect of the pandemic shocks but include the systematic difference between the two types of prefectures (Callaway & Sant'Anna (2021)). We test this using the data prior to the pandemic, i.e., during the period from January to December 2019. Specifically, we regress the amount of purchases, the number of buyers, and the amount of purchases per buyer on the dummy variable for the last half of 2019; the dummy variable for prefectures that declared the state of emergency for more days than the median prefecture (47 days); and the interaction term between the two dummies. SI Table 4 shows that the interaction term is not significantly different from zero in any regressions. Therefore, the pretreatment parallel-trend assumption is satisfied.

The analysis at the prefecture-product level estimates an equation similar to Equation (2) but assumes heterogeneous effects of COVID-19 cases and states of emergency on different products. Conceptually, however, because of rising needs for essential products, particularly health products and foods, the effect on these products is predicted to be greater than that on nonessential products. To test this hypothesis, all the independent variables except for fixed effects are interacted with dummy variables for product categories. Product fixed effects are also included, and city fixed effects are replaced with prefecture fixed effects. Standard errors are clustered at the prefecture and date levels, controlling for correlation between the error terms across products.

Results

City-level analysis

We first run the DID estimation of Equation (2) at the city level and illustrate the results in Figures 5, 6, and 8. Detailed numerical results are presented in SI Table 5.

First, the blue, red, and green dots in the left panel of Figure 5 indicate the point estimates of the effect of each of the five waves of COVID-19 cases on the amount of purchases, the number of buyers, and the amount of purchases per buyer in log, respectively, while lines show corresponding 95-percent confidence intervals. The results reveal a positive and statistically significant effect of the number of COVID-19 cases on online consumption in waves 1 (January-June, 2020) and 2 (June-September, 2020). The point estimates of the effect of the COVID-19 cases in waves 1 and 2 are 0.020 and 0.021, respectively, implying that a doubling of the number of COVID-19 cases per person increased online purchases by approximately two percent. To highlight the size of the effect, we take Shinjuku Ward in Tokyo, a hotspot of COVID-19 cases, as an example. At the beginning of wave 2, June 10, 2020, the number of cases per 1,000 in the ward was 0.0014, and this figure increased to a peak of 0.0264 on August 5. In terms of its log, this is an increase of 2.42. In the same period, online consumption in logs in this ward increased by 1.09. Considering the estimated coefficient of the number of cases, 0.021, these figures imply that 4.6% of the increase in online consumption was due to the increase in COVID-19 cases. Using the average figures across cities, we obtain a similar quantitative result. By stark contrast, the effect of COVID-19 cases in waves 3 (September 202-March 2021), 4 (March-June 2021), and 5 (June-October 2021) is either insignificant or significant but slightly negative. In other words, the number of cases did not affect online consumption one year after the beginning of the pandemic.

The effect on the total amount of purchases can be decomposed into the effect on the number of buyers and on the amount of purchases per buyer. Comparing the blue dots and lines (i.e., the effect on total purchases) with the red and green dots and lines (the number of buyers and purchases per buyer, respectively), we find that the positive effect of the number of cases in the first two waves on purchases is attributed to its positive effect on the number of buyers, not on purchases per buyer. However, it should be emphasized that the number of buyers defined here is the number of buyers in a day. Therefore, it is unclear whether the positive effect on the number of buyers reflects new online shopping platform users or more frequent usage by existing users.

The right panel of Figure 5 presents the effect of states of emergency in different months. Looking at the blue dots and lines, we find that the first state of emergency declared in April 2020 raised the amount of purchases on the online shopping platform by 7.4 percent, while its effect became insignificant one month later in May. Similarly, the second-stage state of emergency had a positive effect on the amount of purchases in the early period in January and February 2021 but lost its positive effect later in March. The effect of the third-stage state of emergency that started in late April 2021 was also positive for the first three months but became insignificant or nearly zero later. The red and green dots and lines in the panel suggest that the positive effect of a state of emergency in its earlier period on the amount of purchases mostly stems from its effect on the number of buyers, not on purchases per buyer. A semi-state of emergency did not affect online purchases (at the bottom of the right panel), possibly because of its less strict regulations.

Comparing the effects of the number of cases and states of emergency, we find that although waves 3-5 of COVID-19 cases in 2021 had no positive effect on online consumption, states of emergency in 2021 had a positive effect, particularly in the early period of each stage. One possible reason for this contrast is that an increase in the number of cases no longer encouraged consumers to stay home one year into the pandemic because they learned to cope with their pandemic-related fears, while states of emergency continued to prompt consumers to stay home and increased the necessity of using online shopping.

Figure 6 presents the effect of the pre- and post-state of emergency periods. In the left panel, we observe that the amount of purchases, the number of buyers, and the amount of purchases per buyer in prefectures in a state of emergency were not systematically different from those in other prefectures three and four weeks before the declaration of a state of emergency in either 2020 or 2021. In contrast, one or two weeks before such a declaration, prefectures that then declared a state of emergency sometimes exhibit higher total purchases, a higher number of buyers, or a higher amount of purchases per buyer than others, possibly because people predicted the future declaration of a state of emergency and thus changed their behaviors one to two weeks prior to the declaration. This result is consistent with the finding from mobile phone data that human mobility started to decline a few weeks before the first state of emergency was declared (Nomura *et al.* (2021); Nagata *et al.* (2021)).

The right panel of Figure 6 shows that the contemporaneous positive effect of a state of emergency on the amount of purchases, and the number of buyers found in the right panel of Figure 5 becomes insignificant or even significantly negative after the state of emergency is lifted. In other words, the effect of a state of emergency on online consumption was temporary and did not persist after its lifting (or after a wave of COVID-19 cases because a state of emergency is usually lifted when the number of cases declines substantially). To further confirm this conclusion, we plot in Figure 7 the relationship between date fixed effects from the estimation of Equation (2), δ_t, and date t and a fitted line using a nonparametric local-linear kernel regression. The figure shows that date fixed effects, or the sum of any time-variant factor that determines online purchases in addition to the number of COVID-19 cases and states of emergency, are stable after the COVID-19 pandemic started in earnest in March 2020. This result suggests that the time trend in online consumption did not change because of the COVID-19 pandemic, confirming its temporary effect on online consumption.

Finally, we find that a state of emergency in neighboring prefectures did not affect online purchases in 2020, although we observe its positive effect in January, February, May, June, and September 2021 (Figure 8). However, unlike the effect of a state of emergency in consumers' own prefectures, the effect of neighboring prefectures' states of emergency did not show a clear declining trend over time. It is still clear that the effect of a state of emergency in a prefecture spills over to its neighbors, possibly because consumers in neighboring prefectures begin preparing for a future state of emergency and thus increase their use of online shopping. Therefore, controlling for the spillover effect is required to estimate the effect of the COVID-19 shocks without biases.

Prefecture-product-level analysis

We now turn to prefecture-product-level analysis to examine heterogeneity in the effect of the COVID-19 shocks across products. Figure 9 shows the effect of the number of COVID-19 cases for each of the four product categories. The upper two panels indicate results for essential products, i.e., (1) health products, health foods, and medicine; and (2) food and household products, whereas the lower two are results for less essential products. According to the blue dots and lines, it is evident that COVID-19 cases had a large positive effect on the purchasing of essential products, while the effect on the purchasing of nonessential products was mostly negative. These results suggest that consumers with pandemic-related fears purchased more essential products online but limited their consumption of nonessential products. The point estimates imply that a doubling of the number of cases resulted in an increase in online purchases of essential products by more than 10% in the first wave. However, the positive effect on essential products declined to insignificant or quite low levels after the third wave. As in the previous analysis, the positive effect on total purchases was mostly attributable to the effect on the number of buyers (red) rather than on purchases per buyer (green).

We also find in Figure 10 that the effect of states of emergency on online purchases (represented by the blue dots) was positive for essential products, except in 2020, but was mostly negative for nonessential products. Moreover, the positive effect on essential products was more persistent over time than the overall effect of states of emergency on total purchases (the right panel of Figure 5) and the effect of COVID-19 cases on purchases of essential products (Figure 9). However, the positive effect eventually disappeared in September 2021.

Finally, Figure 11 shows the effect of the post-state of emergency. The effect of a state of emergency on purchases of health products/foods and medicine 1-4 weeks after it was lifted is positive and mostly insignificant at the 5% level but significant at the 10% level. These findings provide weak evidence that online essential product purchases persistently increased with each state of emergency. However, purchases of other categories of products either did not change or even declined in the post-state-of-emergency period. Because the share of health-related products of total online purchases was not large (Figure 3), the persistent increase in purchases of such products was canceled out by the decrease in purchases of other products, and hence, the effect on total purchases was not significant in the post-state-of-emergency period (the right panel of Figure 6).

Discussion

The results in the previous section suggest that the COVID-19 pandemic stimulated consumption at a major online shopping platform in Japan. This is most likely because consumers facing increasing numbers of positive cases of COVID-19 and declarations of a state of emergency stayed home more and relied more on online shopping than other consumers did. Our further analysis clarifies that the increase in daily online purchases was attributed to an increase in the number of buyers on the platform purchasing essential products, such as health products, foods, and household products. In contrast, the average amount of purchases per buyer did not increase, and amount of purchases of nonessential products often declined during the pandemic. Our findings are quite consistent with those of earlier studies on the pandemic effect on consumption in general (Baker *et al.* (2020); Chronopoulos *et al.* (2020); Di Crosta *et al.* (2021); Gupta *et al.* (2021); Konishi *et al.* (2021); Morikawa (2021a); Nielsen (2022)) and on online consumption (Cruz-Cárdenas *et al.* (2021); Jensen *et al.* (2021); Mason *et al.* (2020); Gao *et al.* (2020); Tran (2021)).

Moreover, their positive effect on online consumption was not persistent but transitory, becoming smaller as consumers became accustomed to the pandemic and disappearing when a wave of the pandemic subsided and states of emergency were lifted. When we examined the effect by product category, we observed heterogeneity in the pandemic effect and weak evidence of a persistent increase in online purchases of health-related products after a state of emergency. However, because nonessential product purchases generally declined after a state of emergency, the total effect in the long run turned out to be zero. In addition, the overall time trend in online shopping utilization did not increase after the pandemic once the temporary effects of the COVID-19 shocks were eliminated.

These results suggest that the pandemic has not permanently changed online consumption behavior in Japan. Consumers purchase more essential products online while they are psychologically and physically constrained, i.e., they stay home because of fear of infection and states of emergency. However, consumers returned to offline shopping once the psychological and physical restrictions are relaxed.

There are two possible reasons for the temporary effect of the pandemic shocks. First, online shopping is quite convenient once users pay initial costs, i.e., setting up accounts and learning how to use the platform. However, compared to offline shopping, online shopping has several disadvantages, such as delayed possession, a lack of social interactions, privacy and security risks, and the difficulty of processing online information (Kim (2020); Cai & Cude (2016); Rohm & Swaminathan (2004); Watanabe & Omori (2020)). Therefore, it is always possible that consumers who are forced to shop online during periods of strong restrictions return to offline shopping when the restrictions are lifted if the variable costs of online shopping are sufficiently high for them. In particular, these costs are presumably higher in Japan than in other countries. According to a survey conducted by McKinsey & Company in June 2020 (Arora *et al.* (2020)), Japanese consumers were more reluctant to make online purchases than consumers in other countries. In addition, a survey by the Ministry of Economy, Trade and Industry in 2020 after the wake of the COVID-19 pandemic found that 88% of respondents were afraid of their private information being exposed through online shopping, a ratio that is not very different from that found in 2017 (Ministry of Economy, Trade and Industry (2022)).

Second, facing a large shock such as the COVID-19 pandemic, people usually react strongly to it at first but their reaction weakens after they learn how to cope with the situation (Di Crosta *et al.* (2021); Guthrie *et al.* (2021); Borbás *et al.* (2021)). Our results clearly show that consumers adapted to the pandemic because we find that the effect of the number of cases and states of emergency diminished over time and finally disappeared. The beginning of the pandemic generated anxiety and fear, which initially drove panic buying and hoarding via online shopping channels (Chronopoulos *et al.* (2020); Nielsen (2022); Keane & Neal (2021); Sheth (2020); Koch *et al.* (2020)), but consumers became accustomed to the pandemic and thus began to reduce such reactions. This presumption is supported by data on human mobility in Japan. Although human mobility declined drastically in the first stage of the first state of emergency. (Yabe *et al.* (2020); Nagata *et al.* (2021)), the decline was limited after the second stage (Okamoto (2021); Nomura *et al.* (2021)). These findings reveal that as consumers experienced several waves of the pandemic and several stages of emergency, they stayed home less and shopped in person more. Therefore, in the long run, consumers are expected to return to the same offline shopping habits as before the pandemic.

Our conclusion is in line with that of an earlier study on Japan by Watanabe et al. using credit-card transaction data (Watanabe & Omori (2020)). However, our analysis differs from theirs in that we use higher-frequency data (daily) for a longer period (January 2019 to October 2021) than theirs with eight time points from January 2019 to October 2020. Accordingly, our data period covers several waves of COVID-19 and several stages of states of emergency in 2021 (Figure 2) that are not covered by Watanabe et al. As a result, we explicitly incorporate the number of COVID-19 cases and states of emergency as determinants of online consumption, finding their diminishing effect over time, and further test whether the effect of the shocks persisted after the shocks were temporarily removed. The analysis of Watanabe et al. is based on transition probabilities of purchasing behavior between several time points and does not test any of these effects statistically. In addition, none of the other studies for other countries examined the effect of the number of cases, states of emergency, or post-states of emergency, taking regional variation of these variables into account (Jensen *et al.* (2021); Mason *et al.* (2020); Gao *et al.* (2020); Tran (2021); Guthrie *et al.* (2021)).

One managerial implication of this study for online shopping platforms is that online sales may decline after the COVID-19 pandemic. To make the temporary increase in online sales during the pandemic persist into the future, more useful tools, such as one-day deliveries and online social communities, should be employed to lower the current costs of online shopping. In addition, using more innovative technologies, such as virtual reality (VR), 3-dimensional (3D) images, and the metaverse, can provide consumers information that can be processed more easily without high cognitive skills (Kim (2020)). Finally, lowering the risks to privacy and security is another key concern.

A policy implication for Japan is that while the importance of digital transformation to economic growth and social welfare has been extensively debated among policy makers and businesses, online shopping, a major part of digital transformation, may not be promoted even after the COVID-19 pandemic, despite any expectations that it will be. Therefore, policy support should be provided to mobilize the efforts in the private sector mentioned above.

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Availability of data and materials

The data supporting the findings of this study are available from Yahoo! Japan, but restrictions apply to the availability of these data, which were used under license for the current study and are not publicly available. Data are, however, available from the authors upon reasonable request and with permission from Yahoo Japan.

Competing interests

The authors declare that they have no competing interests.

Authors' contributions

All authors contributed equally. All authors read and approved the final manuscript.

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Figures

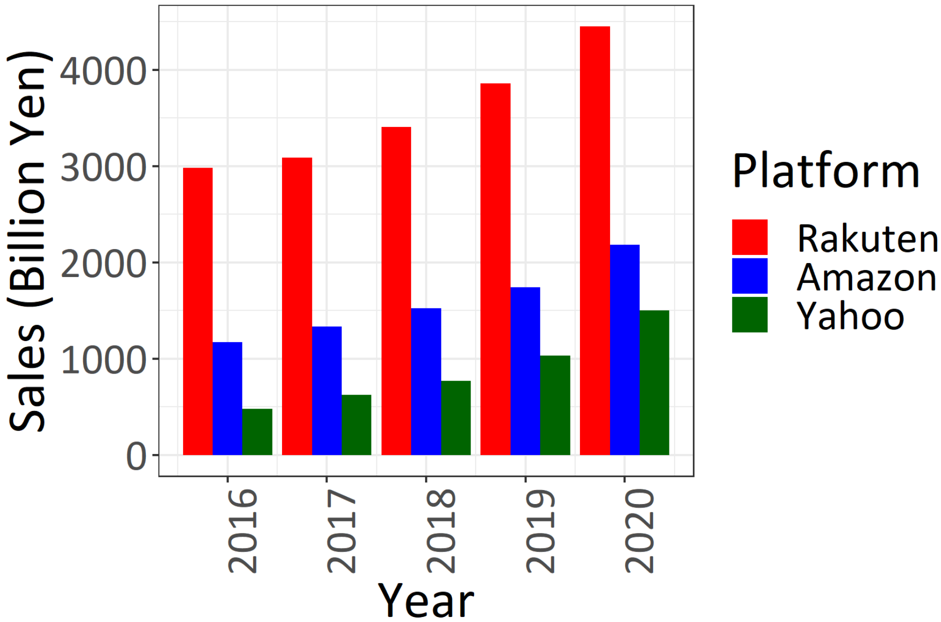

Figure 1: Annual Sales of Top Three Online Platforms. The top three online platforms in Japan are Rakuten Group, Inc., Amazon Japan G.K., and Z Holdings (the parent company of Yahoo! Japan). Note that we use all Amazon Japan sales since Amazon Japan does not publish online shopping sales alone. Data source: (Z Holdings (2022); Rakuten Group, Inc. (2022); U.S. Securities and Exchange Commission (2022)

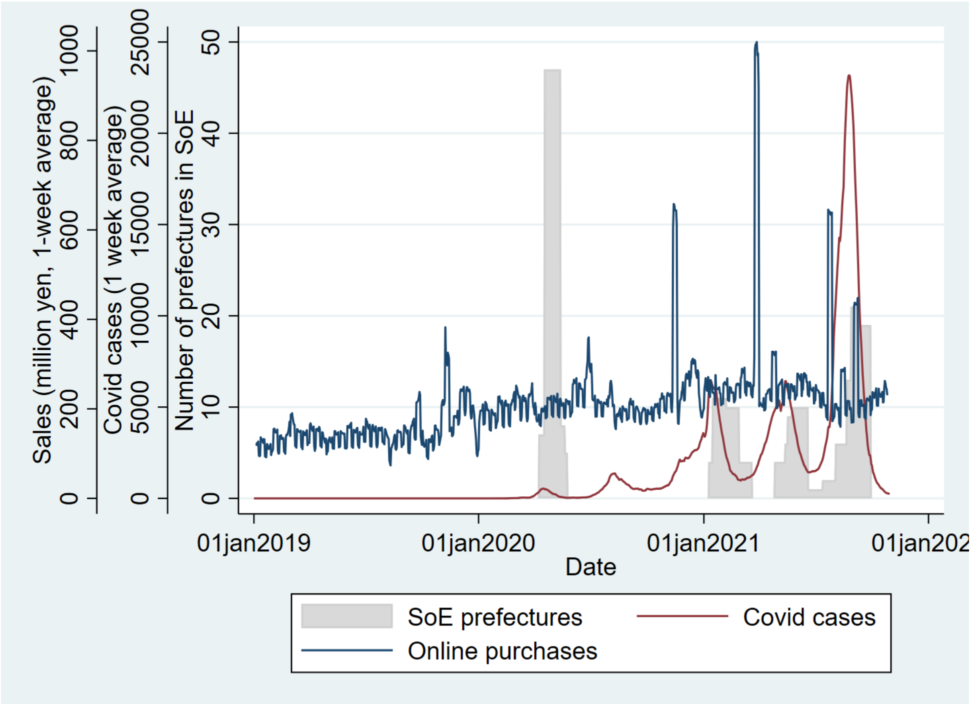

Figure 2: Changes in COVID-19 Cases and Online Purchases and Buyers over Time from January 1, 2019 to October 30, 2021. This figure shows the total number of daily positive COVID-19 cases in Japan averaged over one week (the red line), the number of prefectures in a state of emergency (SoE) due to COVID-19 (the shaded area), and the total number of daily purchases on the online shopping platform in Japan (the blue line). Data source: Ministry of Health, Labor and Welfare (Ministry of Health, Labor and Welfare (2022) and Cabinet Secretariat of Japan (Cabinet Secretariat of Japan (2022)

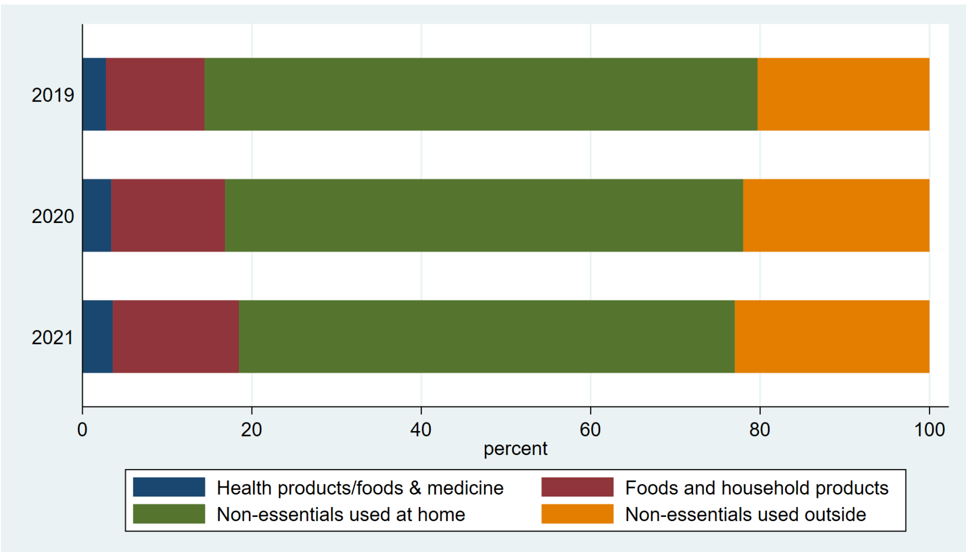

Figure 3: Share of the Amount of Purchases in Each Year by Category and Year. This figure shows the share of each of the four categories of the total amount of purchases on the online shopping site in each year.

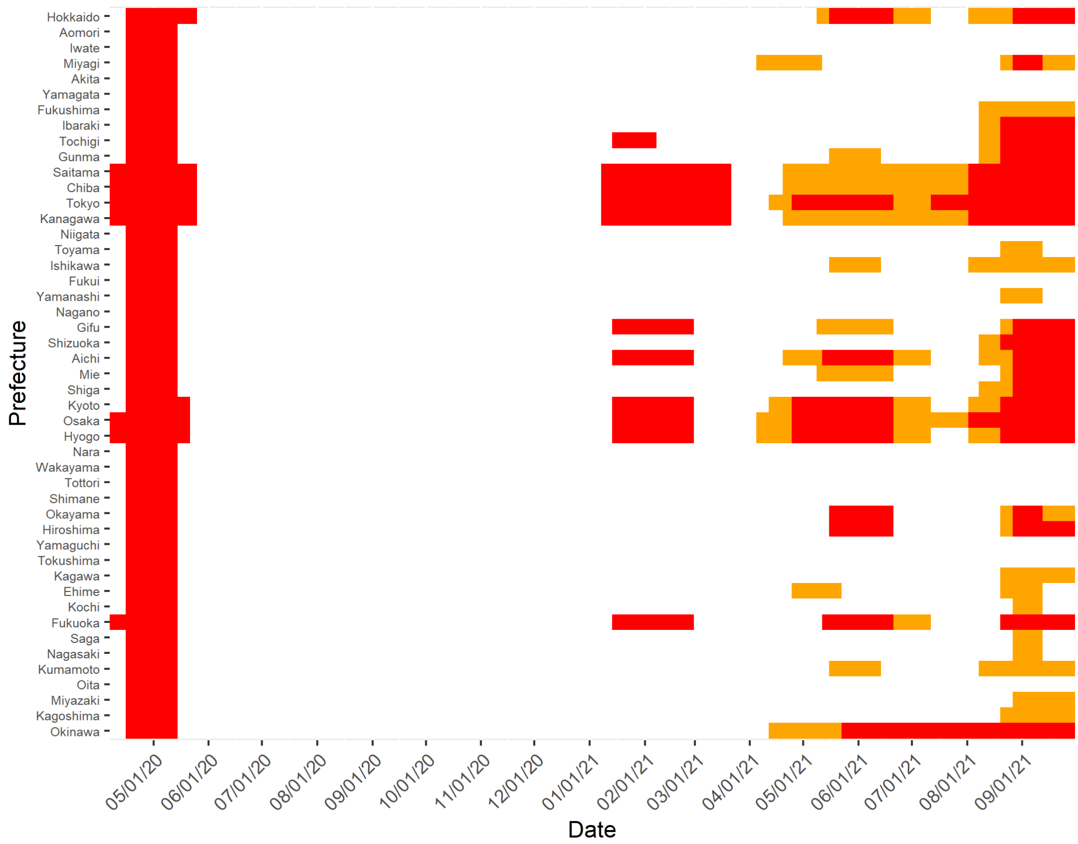

Figure 4: State of Emergency by Prefecture and Week. In this figure, a red cell indicates that the prefecture shown in the first column is in a state of emergency (SoE) in the week shown in the first row, running from the week of April 12, 2020 to that of October 3, 2021, whereas an orange cell indicates that it is in a semi-SoE. The weeks before April 12, 2020, and after October 3, 2021, are omitted because there was no SoE or semi-SoE in these periods. Data source: (Cabinet Secretariat of Japan (2022)

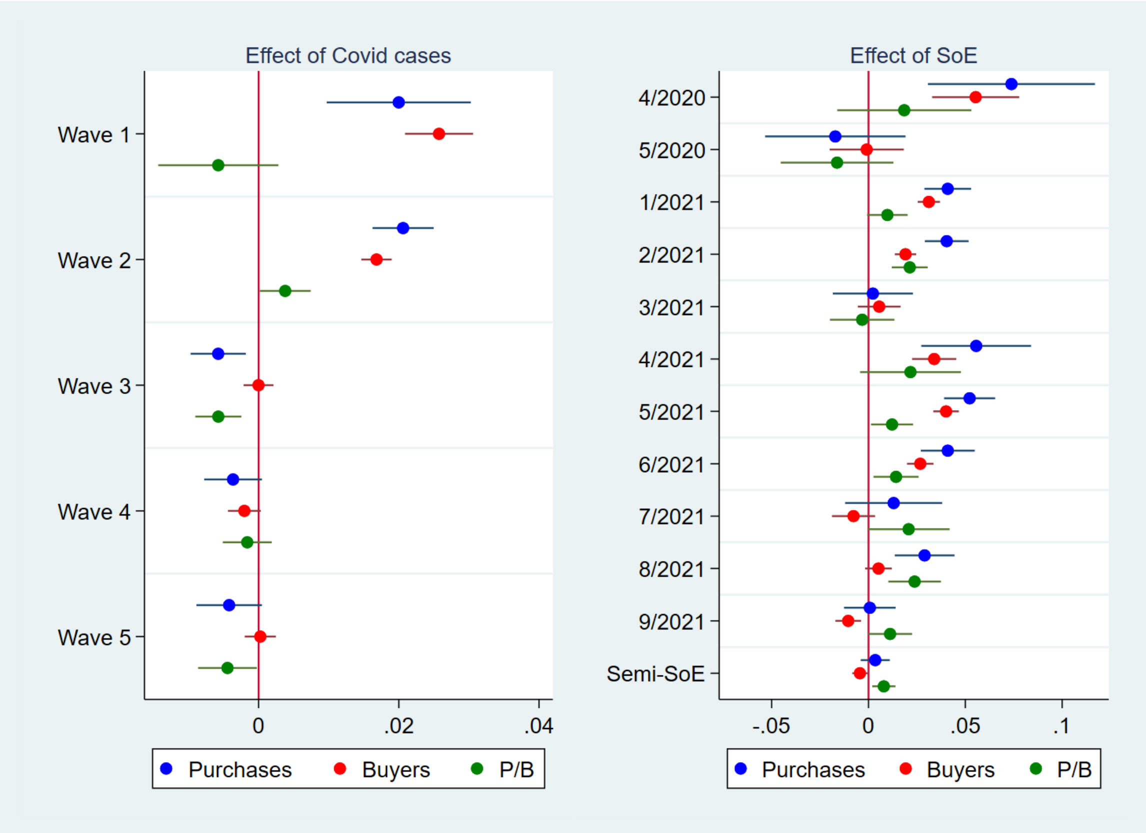

Figure 5: Effects of the Number of COVID-19 Cases and the Declaration of a State of Emergency on the Amount of Purchases, the Number of Buyers, and the Amount of Purchases per Buyer. This figure illustrates the results from the regressions of the amount of purchases, the number of buyers, and the amount of purchases per buyer in logs at the city-date level. The left panel shows point estimates and 95% confidence intervals of the effect of the number of COVID-19 cases per 1,000 persons averaged over one week on the amount of purchases (blue), the number of buyers (red), and the amount of purchases per buyer (green) in the five waves of COVID-19 in the sample period. The right panel shows coefficients and 95% confidence intervals of the declaration of a state of emergency (SoE), separated into the months of the sample period and a semi-SoE, which is less restrictive than an SoE. The number of COVID-19 cases and the declaration of an SoE are given at the prefecture-date level. We take a log of the number of COVID-19 cases per 1,000 persons plus 0.001 to incorporate possible nonlinear relationships. In all regressions, other independent variables are the number of neighboring prefectures in an SoE, dummy variables for 1-4 weeks before and after the declaration of an SoE and a semi-SoE, city fixed effects, date fixed effects, and day-of-the-week fixed effects. Standard errors are clustered at the city level. N=1,091,171.

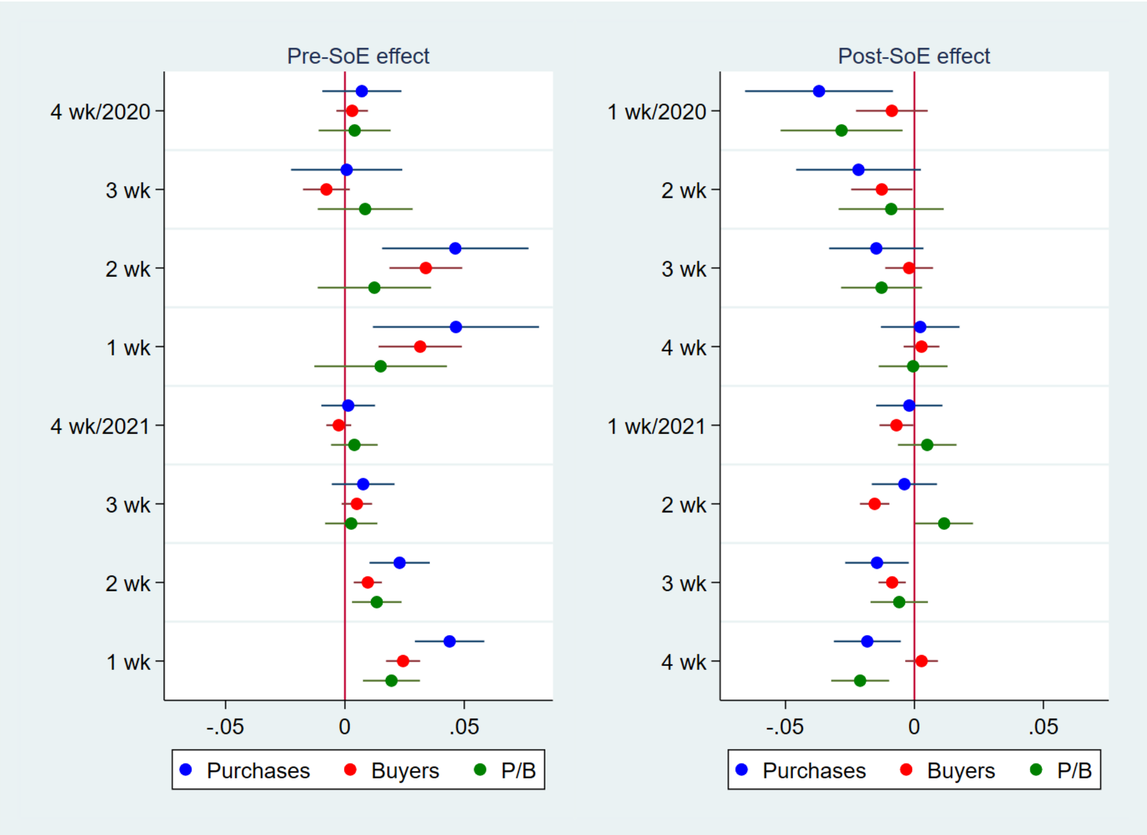

Figure 6: Pre- and Post-treatment Effects of the Declaration of a State of Emergency on the Amount of Purchases, the Number of Buyers, and the Amount of Purchases per Buyer. This figure illustrates the results of the regressions of the amount of purchases, the number of buyers, and the amount of purchases per buyer in logs at the city-date level. The left panel shows point estimates and 95% confidence intervals of dummies for 1-4 weeks before the declaration of a state of emergency (SoE) on the amount of purchases (blue), the number of buyers (red), and the amount of purchases per buyer (green). The right panel shows those of dummies for 1-4 weeks after the end of an SoE. Dummies for before and after an SoE are given at the prefecture-date level. For example, "4 wk/2020" on the x axis of the left panel means 4 weeks before an SoE in 2020, whereas "1wk/2020" in the right panel means 1 week after an SoE in 2020. In all regressions, other independent variables are the number of COVID-19 cases per 1,000 persons, dummies of an SoE, the numbers of neighboring prefectures in an SoE, city fixed effects, date fixed effects, and day-of-the-week fixed effects. Standard errors are clustered at the city level. N=1,091,171.

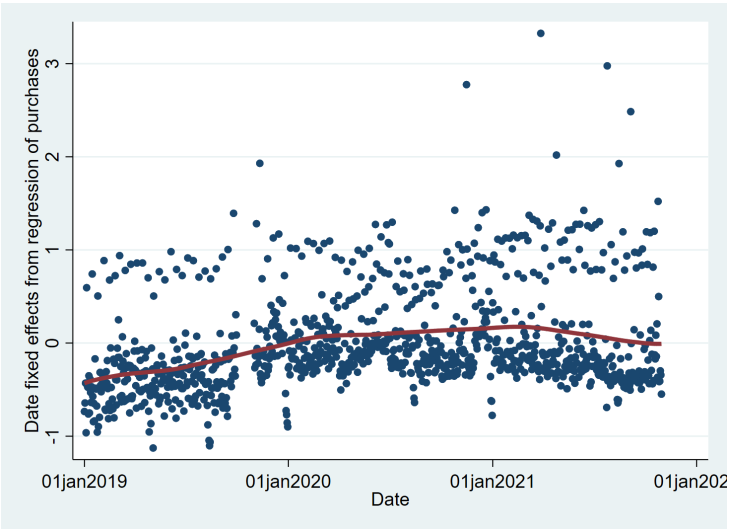

Figure 7: Date Fixed Effects from the Regression of the Amount of Purchases. In this figure, blue dots represent date fixed effects estimated from the regressions of the amount of purchases at the city level for each date, whereas the red line represents the fitted relationship between date fixed effects and dates using a nonparametric local-linear kernel regression. Independent variables are the number of COVID-19 cases per 1,000 persons, the declaration of a state of emergency (SoE), the number of neighboring prefectures in an SoE, dummy variables for 1-4 weeks before and after the declaration of an SoE and a semi-SoE, city fixed effects, date fixed effects, and day-of-the-week fixed effects. Standard errors are clustered at the city level. N=1,091,171.

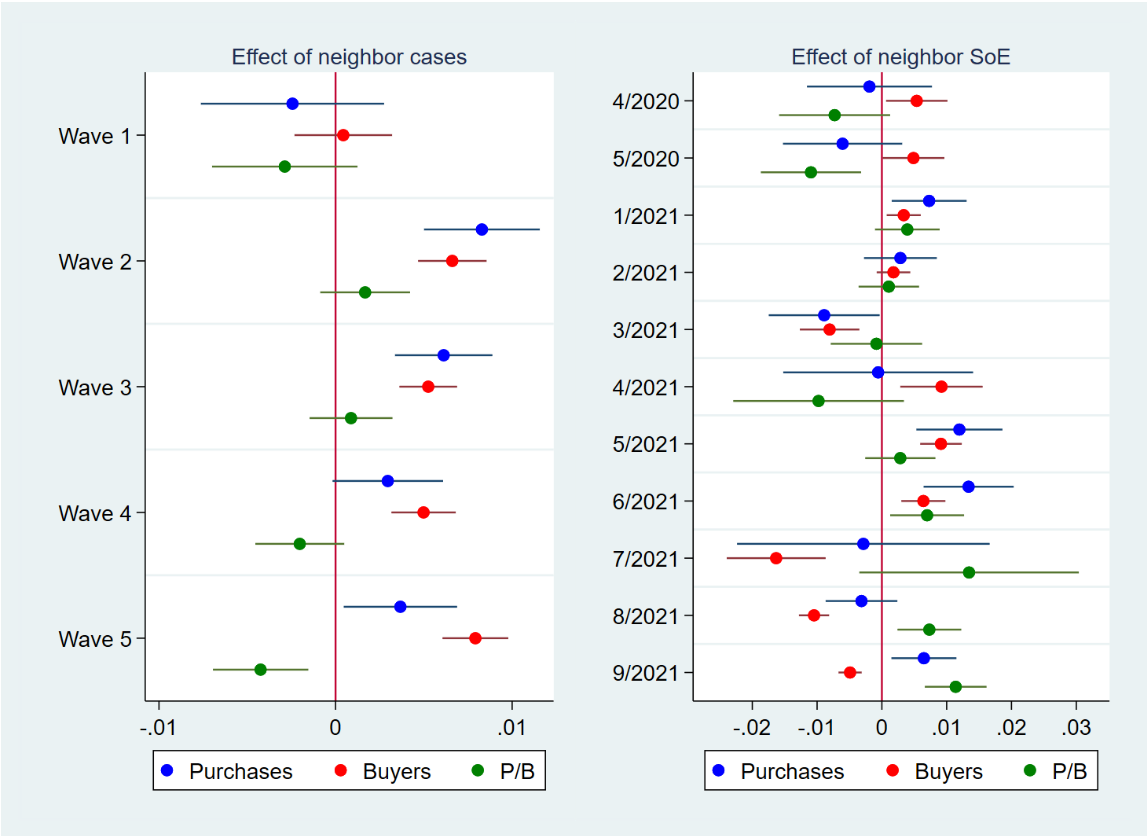

Figure 8: Effects of the Declaration of a State of Emergency in Neighboring Prefectures on the Amount of Purchases, the Number of Buyers, and the Amount of Purchases per Buyer. This figure illustrates point estimates and 95% confidence intervals of the effect of the number of prefectures that were in a state of emergency (SoE) and share any border with the focal prefecture in different months on the amount of purchases (blue), the number of unique buyers (red), and the amount of purchases per unique buyer (green) in logs. In all regressions, other independent variables are the number of COVID-19 cases per 1,000, the dummies of an SoE, the dummies for before and after an SoE, the number of neighboring prefectures in an SoE, city fixed effects, date fixed effects, and day-of-the-week fixed effects. Standard errors are clustered at the city level. N=1,091,171.

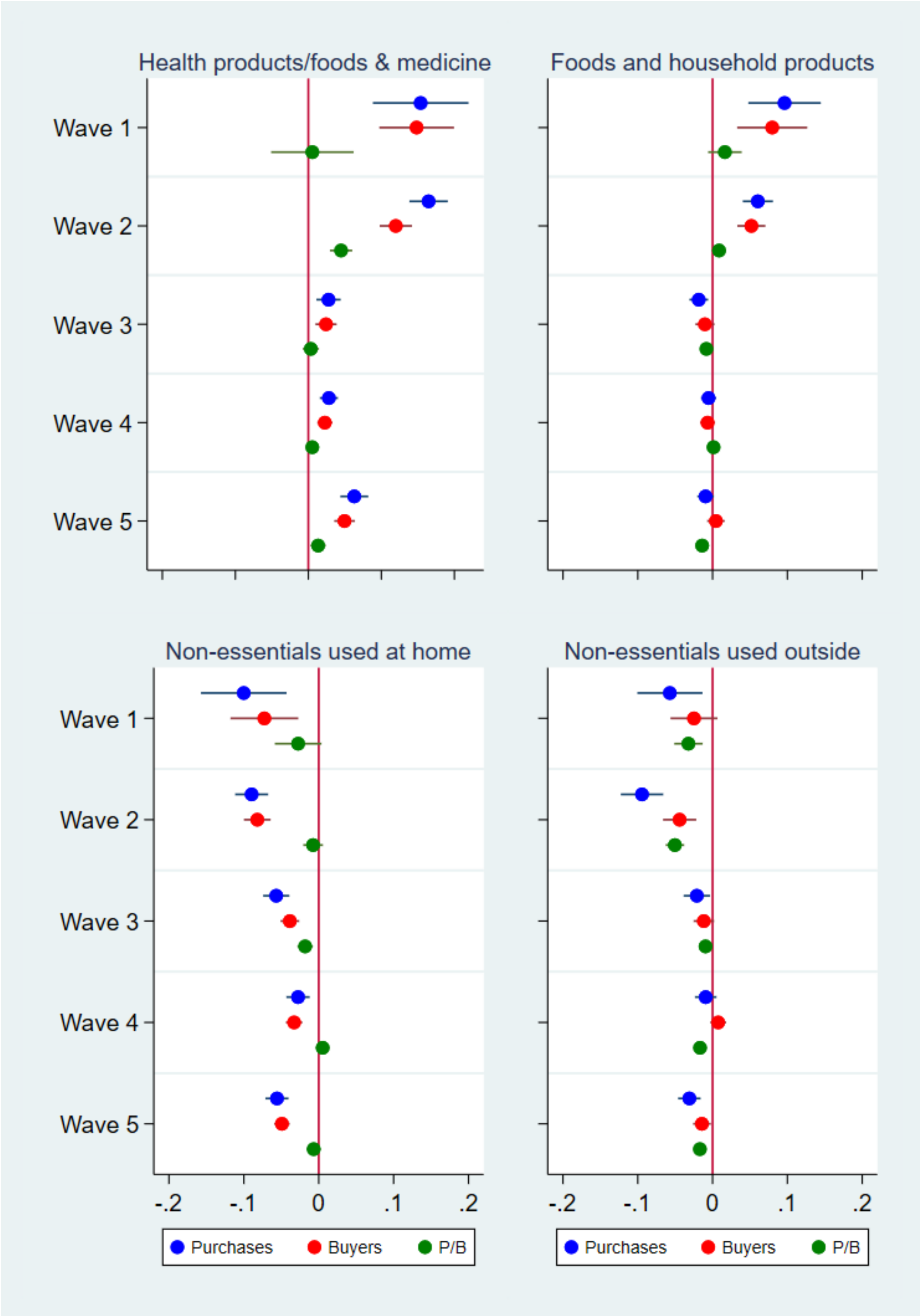

Figure 9: Effects of the Number of COVID-19 Cases on the Amount of Purchases, the Number of Buyers, and the Amount of Purchases per Buyer by Product Category. This figure illustrates the results from the regressions of the amount of purchases, the number of buyers, and the amount of purchases per buyer in logs at the prefecture-product-date level by product category. The dots and lines indicate point estimates and 95% confidence intervals of the effect of the number of COVID-19 cases per 1,000 persons in logs in different waves on the amount of purchases (blue), the number of buyers (red), and the amount of purchases per buyer (green). In all regressions, other independent variables are the dummies of a state of emergency (SoE), the dummies for before and after an SoE, the number of neighboring prefectures in an SoE, prefecture fixed effects, product fixed effects, date fixed effects, and day-of-the-week fixed effects. Standard errors are clustered at the prefecture and date levels. N = 188,437.

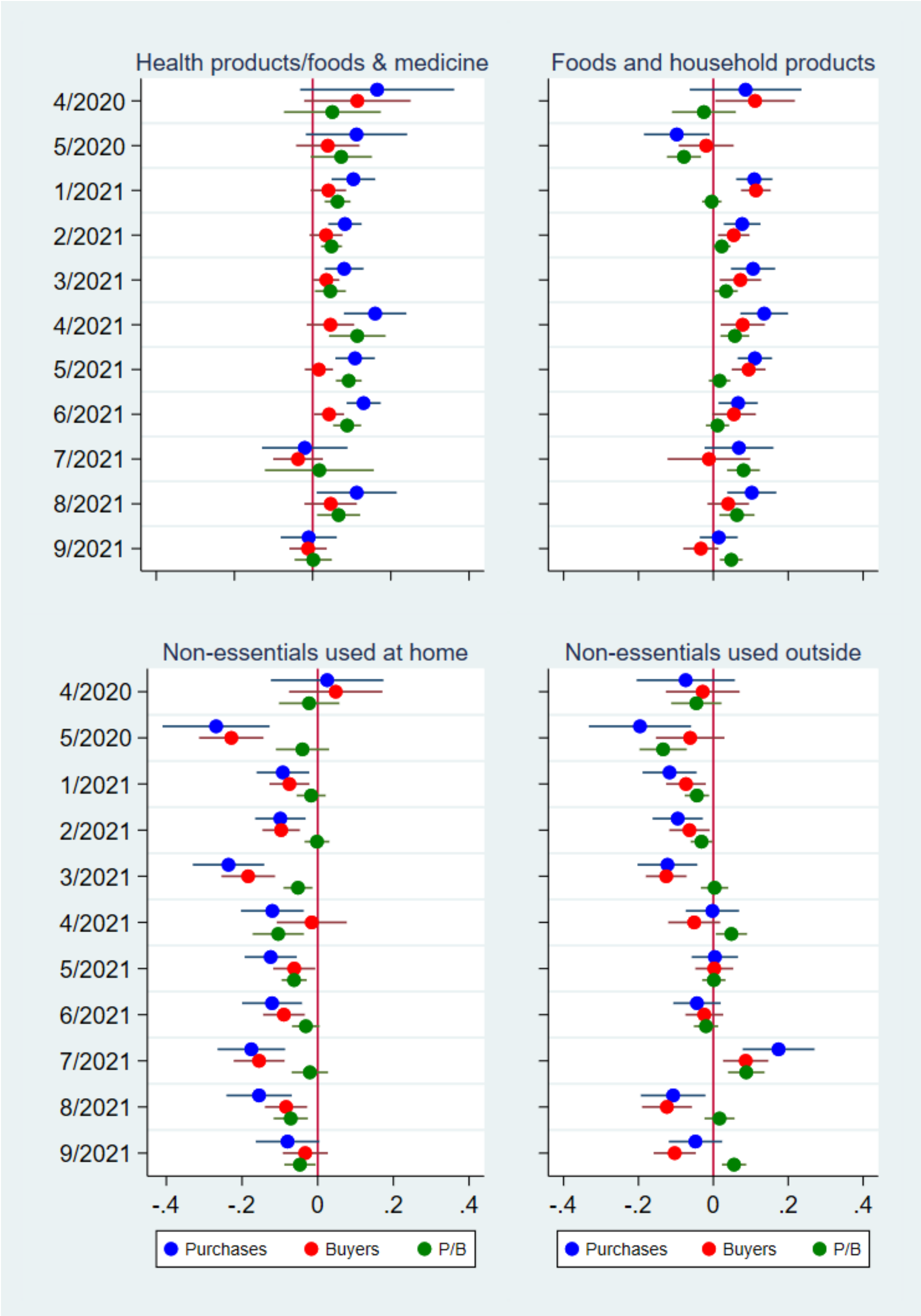

Figure 10: Effects of a State of Emergency on the Amount of Purchases, the Number of Buyers, and the Amount of Purchases per Buyer by Product Category. This figure illustrates the results from the regressions of the amount of purchases, the number of buyers, and the amount of purchases per buyer in logs at the prefecture-product-date level by product category. The dots and lines indicate coefficients and 95% confidence intervals of the effect of dummies for a state of emergency (SoE) in different months on the amount of purchases (blue), the number of buyers (red), and the amount of purchases per buyer (green). In all regressions, other independent variables are the dummies for before and after an SoE, the number of COVID-19 cases per 1,000 persons, the number of neighboring prefectures in an SoE, prefecture fixed effects, product fixed effects, date fixed effects, and day-of-the-week fixed effects. Standard errors are clustered at the prefecture and date levels. N = 188,437.

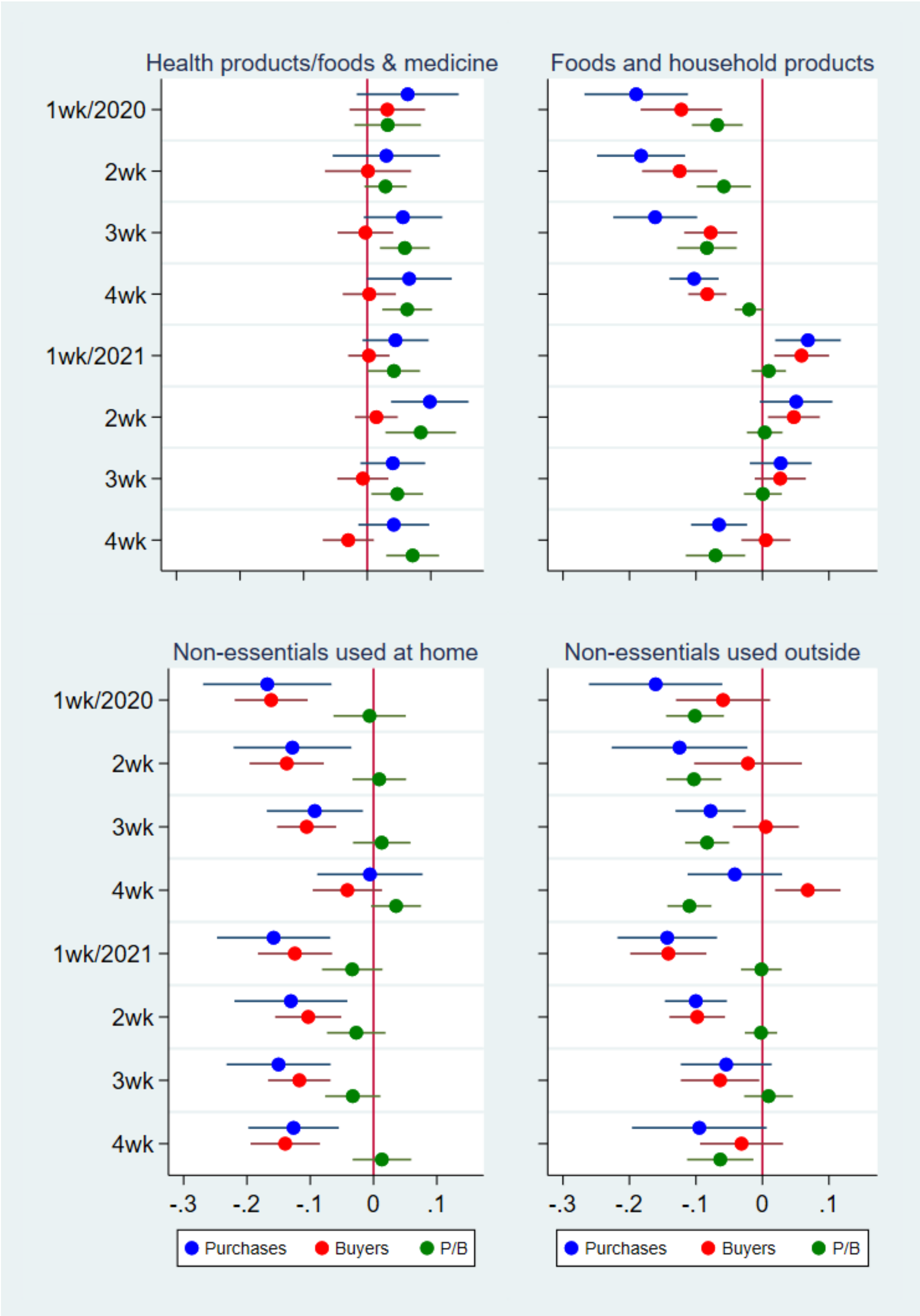

Figure 11: Post-Treatment Effects of a State of Emergency on the Amount of Purchases, the Number of Buyers, and the Amount of Purchases per Buyer by Product Category. This figure illustrates the results from the regressions of the amount of purchases, the number of buyers, and the amount of purchases per buyer in logs at the prefecture-product-date level by product category. The dots and lines indicate coefficients and 95% confidence intervals of the effect of dummies for 1-4 weeks after a state of emergency (SoE) in different months on the amount of purchases (blue), the number of buyers (red), and the amount of purchases per buyer (green). "1wk/2020" on the x-axis means 1 week after an SoE in 2020. In all regressions, other independent variables are the dummies for an SoE, the dummies for before an SoE, the number of COVID-19 cases per 1,000 persons, the number of neighboring prefectures in an SoE, prefecture fixed effects, product fixed effects, date fixed effects, and day-of-the-week fixed effects. Standard errors are clustered at the prefecture and date levels. N = 188,437.

Supplementary Information

Has COVID-19 Permanently Changed Online Consumption Behavior?

SI Table 1: Summary Statistics: Online Purchases at the City Level [1]

	N	Mean	SD	Min	Max
2019	368060	145,423.2	434,547.4	600	46,812,600
2020	380830	206,259.8	690,380.2	800	116,819,900
2021	342281	244,789.0	1,181,328.8	400	200,115,900
Total	1091171	197,825.1	818,192.1	400	200,115,900

[1] This table shows the number of observations (N), mean, standard deviation (SD), minimum (Min) and maximum (Max) of the amount of purchases at the city level by year and in total yen.

SI Table 2: Summary Statistics: Number of Positive Cases of COVID-19 per 1,000 at the City Level [1]

	N	Mean	SD	Min	Max
2019	368060	0.00000	0.00000	0	0
2020	380830	0.00395	0.00775	0	.0679338
2021	342281	0.03152	0.04866	0	.4702274
Total	1091171	0.01127	0.03088	0	.4702274

[1] This table shows the number of observations (N), mean, standard deviation (SD), minimum (Min) and maximum (Max) of the number of positive cases of COVID-19 per 1,000 at the city level by year and in total.

SI Table 3: Summary statistics: Number of Positive Cases of COVID-19 per 1,000 in log at the City Level [1]

	N	Mean	SD	Min	Max
2019	368060	-6.908	0.000	-6.907755	-6.907755
2020	380830	-5.995	1.046	-6.907755	-2.674608
2021	342281	-4.157	1.223	-6.907755	-.7524145
Total	1091171	-5.726	1.456	-6.907755	-.7524145

[1] This table shows the number of observations (N), mean, standard deviation (SD), minimum (Min) and maximum (Max) of the number of positive cases of COVID-19 per 1,000 in log at the city level by year and in total.

SI Table 4: Results of Checking for Parallel Trends Prior to the Treatment [1]

Dependent variables	(1) Purchases	(2) Buyers	(3) Purchases per buyer
LastHalf2019	-0.175**	-0.0976**	-0.0774**
	(0.00401)	(0.00296)	(0.00263)
FrequentSoE	0.710**	0.724**	-0.0142**
	(0.0620)	(0.0612)	(0.00510)
LastHalf2019XFrequentSoE	0.00427	0.00388	0.000387
	(0.00505)	(0.00382)	(0.00325)
Observations	368,060	368,060	368,060
R-squared	0.082	0.096	0.020

[1] This table shows results from the regression of the amount of purchases (column 1), the number of buyers (2), and the amount of purchases per buyer (3). LastHalf2019 and FrequentSoE indicate the dummy variable for the last half of 2019 and the dummy variable for prefectures that were in a state of emergency for longer period than the median prefecture (47), respectively. LastHalf2019XFrequentSoE is the interaction term between the two. Standard errors clustered at the city level are in parentheses. ** $p<0.01$, * $p<0.05$.

SI Table 5: Results of Equation (2) [1]

Dependent variables	(1) Purchases	(2) Buyers	(3) Purchases per buyer
Cases in wave 1	0.0200**	0.0257**	-0.00575
	(0.00524)	(0.00248)	(0.00437)
Cases in wave 2	0.0206**	0.0168**	0.00379*
	(0.00222)	(0.00111)	(0.00185)
Cases in wave 3	-0.00576**	-1.42e-05	-0.00575**
	(0.00201)	(0.00109)	(0.00167)
Cases in wave 4	-0.00365	-0.00203	-0.00162
	(0.00210)	(0.00120)	(0.00178)
Cases in wave 5	-0.00420	0.000239	-0.00444*
	(0.00238)	(0.00114)	(0.00214)
SoE in 04/2020	0.0738**	0.0554**	0.0185
	(0.0220)	(0.0115)	(0.0177)
SoE in 05/2020	-0.0172	-0.000918	-0.0162
	(0.0185)	(0.00977)	(0.0148)
SoE in 01/2021	0.0409**	0.0312**	0.00975
	(0.00615)	(0.00294)	(0.00534)
SoE in 02/2021	0.0404**	0.0191**	0.0213**
	(0.00576)	(0.00282)	(0.00474)
SoE in 03/2021	0.00226	0.00553	-0.00326
	(0.0105)	(0.00564)	(0.00849)
SoE in 04/2021	0.0556**	0.0339**	0.0217
	(0.0145)	(0.00583)	(0.0133)
SoE in 05/2021	0.0522**	0.0401**	0.0122*
	(0.00673)	(0.00337)	(0.00555)
SoE in 06/2021	0.0409**	0.0267**	0.0142*
	(0.00710)	(0.00349)	(0.00594)
SoE in 07/2021	0.0130	-0.00775	0.0207
	(0.0128)	(0.00569)	(0.0108)
SoE in 08/2021	0.0290**	0.00516	0.0238**
	(0.00787)	(0.00353)	(0.00693)
SoE in 09/2021	0.000685	-0.0105**	0.0112
	(0.00679)	(0.00338)	(0.00579)
Semi-SoE	0.00349	-0.00442*	0.00791*
	(0.00383)	(0.00203)	(0.00307)
SoE in 2020 before 4w	0.00710	0.00304	0.00407
	(0.00846)	(0.00337)	(0.00769)
SoE in 2020 before 3w	0.000734	-0.00776	0.00850
	(0.0119)	(0.00500)	(0.0101)
SoE in 2020 before 2w	0.0463**	0.0339**	0.0124
	(0.0156)	(0.00778)	(0.0121)
SoE in 2020 before 1w	0.0465**	0.0316**	0.0150
	(0.0177)	(0.00890)	(0.0142)
SoE in 20201 before 4w	0.00138	-0.00259	0.00397
	(0.00573)	(0.00266)	(0.00498)
SoE in 20201 before 3w	0.00765	0.00501	0.00264
	(0.00671)	(0.00325)	(0.00558)
SoE in 20201 before 2w	0.0229**	0.00960**	0.0134*
	(0.00644)	(0.00302)	(0.00530)
SoE in 20201 before 1w	0.0439**	0.0244**	0.0195**
	(0.00742)	(0.00365)	(0.00609)
Semi-SoE before 4w	-0.000108	-0.00107	0.000964
	(0.00522)	(0.00238)	(0.00451)
Semi-SoE before 3w	-0.00906	-0.00460	-0.00446
	(0.00511)	(0.00244)	(0.00442)
Semi-SoE before 2w	0.00351	-0.00396	0.00747
	(0.00507)	(0.00249)	(0.00445)
Semi-SoE before 1w	0.00798	0.00275	0.00523

	(0.00600)	(0.00277)	(0.00509)
SoE in 2020 after 1w	-0.0370*	-0.00875	-0.0282*
	(0.0146)	(0.00709)	(0.0121)
SoE in 2020 after 2w	-0.0217	-0.0127*	-0.00901
	(0.0123)	(0.00605)	(0.0104)
SoE in 2020 after 3w	-0.0148	-0.00205	-0.0127
	(0.00932)	(0.00473)	(0.00800)
SoE in 2020 after 4w	0.00224	0.00275	-0.000510
	(0.00777)	(0.00353)	(0.00680)
SoE in 20201 after 1w	-0.00200	-0.00696*	0.00496
	(0.00655)	(0.00336)	(0.00579)
SoE in 20201 after 2w	-0.00388	-0.0154**	0.0115*
	(0.00645)	(0.00291)	(0.00570)
SoE in 20201 after 3w	-0.0145*	-0.00863**	-0.00589
	(0.00628)	(0.00270)	(0.00567)
SoE in 20201 after 4w	-0.0183**	0.00277	-0.0210**
	(0.00662)	(0.00323)	(0.00572)
Semi-SoE after 1w	-0.00884	-0.00668	-0.00216
	(0.00736)	(0.00341)	(0.00635)
Semi-SoE after 2w	-0.000298	-0.000557	0.000260
	(0.00785)	(0.00315)	(0.00703)
Semi-SoE after 3w	0.00684	0.000996	0.00584
	(0.00716)	(0.00321)	(0.00621)
Semi-SoE after 4w	0.000203	-0.00135	0.00155
	(0.00671)	(0.00290)	(0.00614)
Neighbor Cases in wave 1	-0.00244	0.000437	-0.00288
	(0.00264)	(0.00141)	(0.00210)
Neighbor Cases in wave 2	0.00829**	0.00661**	0.00168
	(0.00167)	(0.000989)	(0.00130)
Neighbor Cases in wave 3	0.00612**	0.00525**	0.000876
	(0.00141)	(0.000834)	(0.00120)
Neighbor Cases in wave 4	0.00296	0.00498**	-0.00203
	(0.00160)	(0.000929)	(0.00128)
Neighbor Cases in wave 5	0.00367*	0.00792**	-0.00425**
	(0.00164)	(0.000950)	(0.00138)
Neighbor SoE in 04/2020	-0.00191	0.00538*	-0.00729
	(0.00492)	(0.00242)	(0.00437)
Neighbor SoE in 05/2020	-0.00606	0.00488*	-0.0109**
	(0.00469)	(0.00243)	(0.00394)
Neighbor SoE in 01/2021	0.00730*	0.00337*	0.00393
	(0.00295)	(0.00134)	(0.00254)
Neighbor SoE in 02/2021	0.00286	0.00179	0.00107
	(0.00286)	(0.00132)	(0.00238)
Neighbor SoE in 03/2021	-0.00890*	-0.00806**	-0.000839
	(0.00436)	(0.00234)	(0.00359)
Neighbor SoE in 04/2021	-0.000572	0.00920**	-0.00977
	(0.00747)	(0.00324)	(0.00671)
Neighbor SoE in 05/2021	0.0120**	0.00912**	0.00284
	(0.00338)	(0.00164)	(0.00276)
Neighbor SoE in 06/2021	0.0134**	0.00641**	0.00698*
	(0.00354)	(0.00173)	(0.00291)
Neighbor SoE in 07/2021	-0.00286	-0.0163**	0.0135
	(0.00994)	(0.00389)	(0.00863)
Neighbor SoE in 08/2021	-0.00314	-0.0105**	0.00733**
	(0.00282)	(0.00119)	(0.00251)
Neighbor SoE in 09/2021	0.00649*	-0.00491**	0.0114**
	(0.00256)	(0.000911)	(0.00243)
Neighbor Semi-SoE	-7.96e-05	-0.00557**	0.00549**
	(0.00162)	(0.000794)	(0.00138)
Observations	1,091,171	1,091,171	1,091,171
R-squared	0.912	0.980	0.216

[1] This table shows the results from the regression of the amount of purchases (column 1), the number of buyers (2), and the amount of purchases per buyer (3) using Equation (2). "Cases" and "SoE" respectively mean the number of COVID-19 cases and the declaration of a state of emergency. "Neighbor" indicates the number of cases or the declaration of an SoE in neighboring prefectures, whereas "before iw" and "after iw" represent i weeks before and after an SoE, respectively. Standard errors clustered at the city level are in parentheses. ** $p<0.01$, * $p<0.05$.