Japanese Journal of Monetary and Financial Economics Vol. 10, pp. 2-18, 2022

How the COVID-19 Pandemic Changed Consumer Lifestyle: Evidence from High-Frequency Panel Data in Japan

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ABSTRACT

The COVID-19 pandemic has had a significant impact on consumer behavior and lifestyle. After the outbreak, people increased their daily spending at supermarkets and drugstores near their homes but reduced it on dining out and entertainment activities around urban offices. Additionally, they increased their use of online shopping and cashless payments. This study examines how consumer behavior changed before and during the COVID-19 pandemic in terms of expenditure items, store categories, payment methods, and purchase times, as well as the attributes of consumers associated with these changes using high-frequency purchasing panel data in Japan. In conclusion, since the outbreak of the pandemic, consumption in general has declined, especially amongst high-income consumers who save because of fewer opportunities for face-to-face consumption. The study also shows that single young women have increased their online consumption, while the gender gap in purchasing at supermarkets, drugstores and department stores has decreased. Furthermore, we find that there is generally no significant relationship between family structure and consumption. This may suggest that apart from government cash transfers, ensuring consumption opportunities is important for the recovery of consumption.

Key words: COVID-19 and consumer behavior, online shopping, cashless payments, cash transfer policy, household production

JEL Classification: G50, D12, D91

1. Introduction

The COVID-19 has had a significant impact on consumer behavior. In particular, it had a significant negative impact on face-to-face consumption (dining out, travel etc.). In addition, the prolonged COVID-19 pandemic is to have affected not only changes in consumer spending, but also the consumer lifestyles in general.

For example, the government's request for self-restraint and the introduction of telework are presumed to have led to a decrease in shopping and drinking around offices, and an increase in shopping at stores near home and online shopping. In addition, the prolonged stay at home may have affected household production.

In this study, we will statistically examine the changes in consumer behavior before and during COVID-19 from various perspectives and indicators. The data used here is Macromill's "Omni-directional Consumer Panel Survey (MHS)". This MHS data is a panel format database of survey participants' attributes (gender, age, household income, family structure, occupation) and purchase records (when, where, what, how much, and with what payment method), using their purchase receipts, with the consent of the participants for the collection and use of the data.

In conclusion, after the outbreak, general consumption has decreased, especially in items such as dining out, entertainment, and transportation. On the other hand, the use of supermarkets, drugstores, and online shopping has increased. In addition, earlier purchase times during the day and an increase in cashless payments were observed. In terms of consumer attributes, we found that single women have increased their use of online shopping, and that the gender gap in daily shopping around their home (e.g., at supermarkets) has decreased. We also saw that the higher the income, the more the COVID-19 has changed their consumption behavior. In particular, there was a significant decrease in dining out, entertainment, transportation, and department stores, suggesting that the decrease in face-to-face consumption opportunities is directly related to the decrease in consumption (high-value) expenditure. These results suggest that other than providing monetary benefits to the middle- and lower-income groups, ensuring consumption opportunities is important for the recovery of solid consumption.

There are many previous studies on the impact of COVID-19 on consumption.

Watanabe and Omori (2020a) analyzed the suppression of service consumption using credit card transaction history data. They noticed a large decline in eating out, travel, lodging, and entertainment, and the impact of the decline in consumer consumption in their late 30s to early 50s was considerable. Similarly, Konishi et al. (2021) used point of sale (POS) data (supermarkets, convenience stores, home centers, drug stores, and electronics mass merchandisers) to investigate the changes in consumption due to COVID-19. They found an increase in the sale of masks, alcohol disinfectants, computers for telecommuting, and food in supermarkets; and a decrease in eating out and sales of cosmetics.

Watanabe and Omori (2020b) also analyzed trends in online consumption using the same credit card transaction history data mentioned earlier. While those who had been online before the pandemic outbreak (defined by whether they used online consumption, not by the amount spent) increased their online consumption, those who consumed online in the wake of the pandemic did not increase their online consumption to the same extent, suggesting that they might return to offline consumption once the pandemic is over.

Yabu and Watanabe (2021) analyzed the change in the percentage of people who stayed at home during COVID-19 using location information from smartphones. They estimated that 1/4 of the respondents refrained from going out because of government requests and 3/4, due to fear of infection. As for going out, Fujii and Nakata (2021) analyzed the relationship between mobility and GDP using Google mobility data.

Nakata (2021) conducted an online questionnaire survey of the same monitor at multiple points to analyze whether the risk of infection was higher among people who traveled. The results indicated that the risk of infection is higher among young people, men, and those who have frequent contact with friends and acquaintances, whereas the risk of infection is lower among older people and women.

Yamamura and Tsutsui (2020) analyzed the mental state and preventive behavior of monitors through multiple online surveys. They found that the declaration of a state of emergency gave rise to feelings of confinement at home, anger, fear, and anxiety, and that women had stronger preventive behavior against the infection than men.

Kikuchi, Kitao, and Mikoshiba (2021) analyzed the impact of COVID-19 on employment and income and determined that the effect depended on age, gender, employment type, education, industry, and occupation. The impact was greater among non-regular employees and younger people, especially among women, single people, and part-time employees in the face-to-face service industry[1].

Ishii, Nakayama, and Yamamoto (2020) found that college graduates, full-time employees, and those working for large companies were able to easily transition to online work and have lower levels of income insecurity than other types of employees.

These studies indicate that the impact of COVID-19 on consumption is influenced by differences in individual consumer attributes and psychological factors.

The effects of government policies on COVID-19 have also been studied. Kubota, Onishi, and Toyama (2021) analyzed the effects of government cash transfers (Special Cash Payment, SCP) on household consumption using personal bank account data. They revealed that the timing of benefit payments from the government varies widely across households, the effect of expenditure stimulus lasts for more than a month, but the marginal propensity to consume is 0.49 over six weeks. The expenditure stimulus effect depends on the economic status of consumers, especially their holdings of liquid assets. Kaneda, Kubota, and Tanaka (2021) also estimate the bounds (lower and upper bounds) of the marginal propensity to consume using data from Money Forward ME, a smartphone app for personal finance management. Both studies have in common the use of cash withdrawals from bank accounts as a proxy variable for consumption expenditure.

Baker et al. (2020) examined the consumption response to cash transfers under the Coronavirus Assistance, Relief, and Economic Security (CARES) Act in the United States (U.S.). Coibion, Gorodnichenko, and Weber (2020) analyzed the CARES Act through a large-scale survey, and Misra, Singh, and Zhang (2021) verified the results using debit card transaction data. Feldman and Heffetz (2021) conducted a comparative study of cash transfers in Israel and worldwide. Existing research on the consumer impact of COVID-19 is diverse.

To analyze changes in consumer behavior from a more multifaceted perspective, this study focuses on changes in consumption items and consumption styles (e.g., which stores are favored by consumers, whether they use online shopping or cashless payment, and whether there are changes in the time of day they shop). We also examine how these changes are affected by differences in consumer attributes (age, gender, household income, number of family members, and occupation).

This study offers multiple contributions to the literature on COVID-19 and changes in consumer behavior. First, this study uses more detailed panel data than existing studies and examine changes in consumer behavior from a broad perspective. While previous studies have used data on only specific credit cards and bank accounts, this study includes data on a variety of payment methods (cash, IC cards, mobile payments, etc.), individual consumption items and amounts spent in stores, actual purchases for online shopping, and amounts spent at different times of the day. Second, the analysis covers a relatively longer period than previous studies and analyzes the effect of the impact of various attributes on consumer behavior, before the pandemic, under the declaration of a state of emergency, and after the declaration was lifted. In particular, among the various constraints on consumers under the COVID-19, we found that the higher the income, the more the decrease in consumption due to the loss of consumption opportunities, and that family structure (number of family members, number of children in a family) did not have a significant impact on consumer behavior. These results may provide some insight into how to revitalize consumption under the COVID-19 in Japan.

This paper is organized as follows. Section 2 describes the data and analytical framework used in this study. Section 3 presents the results of the panel data regression analysis and examines how COVID-19 changed consumer behavior. Section 4 summarizes the study, discusses its limitations, and provides direction for future research.

2. Data and Estimation Model

2.1. Data

The consumer purchase data used in this study are the Household Panel Survey (Macromill's Holistic Consumer Panel Survey, MHS) provided by Macromill, Inc.

This MHS data is a panel format database of survey participants' attributes (gender, age, household income, family structure, occupation) and purchase records (when, where, what, how much, and with what payment method), using their purchase receipts, with the consent of the participants, and contains more than 30 million transactions per year, of approximately 20,000 monitors.

As for the attributes of the monitors, the data includes gender, age, household income, prefecture of residence, family structure (number of family members, number of children (under 18 years old) in the family, number of elderly (over 60 years old)), and occupation. Each monitor (who) is anonymized, and in order to reduce the risk of further identification, the database is designed so that the sample size for each attribute is not extremely small.

The data used in this study are superior to those used in earlier studies in several ways as we stated. First, while studies using credit card transaction histories can only observe purchasing behavior in stores with credit cards and POS systems, the database used in this study includes payment methods other than credit cards (cash, IC cards, mobile payments, etc.) and purchase data other than POS system, thus covering a wider range. Second, the data are constructed as panel data. That is, for each specific monitor, data includes time of purchase, store of purchase, item of purchase, and means of payment along with monitor attributes. However, this data has the problem that the amount of recorded purchase data varies from monitor to monitor. In other words, some monitors consistently record purchase data every month, while others do not. Therefore, the sample monitors in this study are based on three selection criteria[2]. The sample period was from November 2019 to January 2021, and monthly aggregate values were used to avoid serial correlation of purchase data[3]. The number of monitors selected based on the above conditions was 1,424, and a total of 21,360 data were observed. In addition, as for the attributes for monitor, the data is updated once a year in principle, so, the following study treats consumer attributes as time-invariant variables.

2.2. Estimation Model

Here, we define multiple indicators of changes in consumer behavior and statistically examine how these indicators have changed since the COVID-19 outbreak, controlling for consumer attributes and other factors (age, gender, family structure, and household income).

Specifically, we estimate the following regression equation.

$$Expediture\ index = f(aftercovid\ \ panel\ ID\ attributes,\ aftercovid \times panel\ ID\ attributes) + u_i$$

The following 11 indices[4] related to consumption behavior were used as dependent variables.

Expenditure: Amount of consumption expenditure (monthly data)
EC rate: Online consumption expenditure/*Expenditure*
Dining out rate: Dining out expenditure/*Expenditure*
Entertainment rate: Entertainment expenditure/*Expenditure*
Transportation rate: Transportation expenditure/*Expenditure*
Housing and home rate: Housing and home appliance expenditure/*Expenditure*
Supermarket rate: Purchases at supermarkets/*Expenditure*
Drugstore rate: Purchases at drugstores/*Expenditure*
Department store rate: Purchases at department stores/*Expenditure*
Cashless rate: Percentage of the amount paid by non-cash payment methods
MPurchase time: Weighted average of purchase times (mean of the purchase time weighted by percentage of expenditure at that time).

Figure 1 shows the distribution of purchase times during a day (share in terms of expenditure[5], calculated on a monthly basis) for all sample consumers in January and May 2020 and January 2021. After the COVID-19 outbreak, we can see that the distribution of purchase time shifts from right to left (i.e., purchase time has become earlier). In particular, comparing January 2020 and January 2021, the percentage of consumption expenditure between 18:00 and 23:00 has decreased.

Next, we use the following consumer attributes as explanatory variables. We also use a dummy variable (*aftercovid*) to determine whether there was any change after the COVID-19 outbreak.

Age: actual age of the consumer/monitor
Female: dummy variable that is set to 1 if the gender is female.
FamilyNum: number of family members
ChildNum: number of children in the family (under 18 years old)

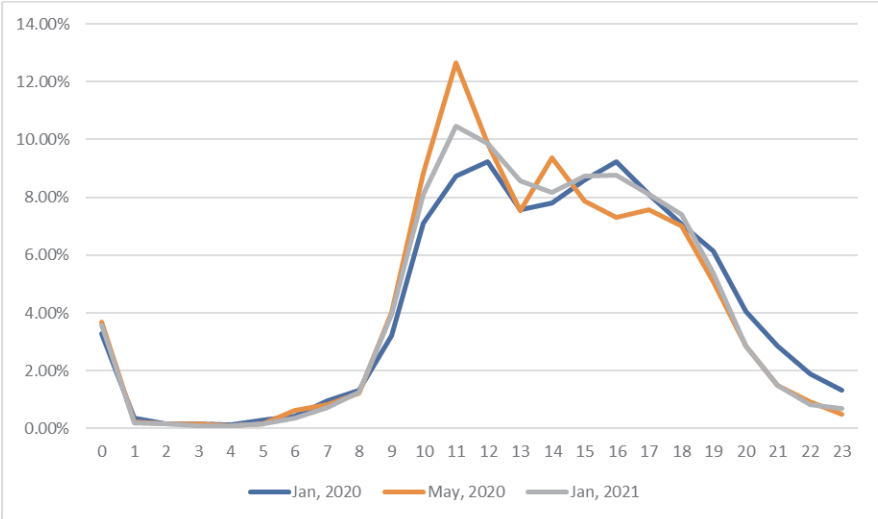

Fig. 1. Changes in the timing of purchase during a day
The shift of the distribution of consumers' purchasing time during a day (percentage of monthly expenditure by hours, January 2020, May 2020, and January 2021).

HouseholdIncome: level of household income (9 levels[6])

Jobdummy: occupation dummy (12 types[7])

aftercovid: a dummy variable that is set to 1 after April 2020

Consumer attribute variables are those collected (reported) by the survey monitors at the beginning of the sample period, and are treated as unchanged during the estimation period, although changes may exist (e.g., age and other factors such as income, family structure, and job/employment which may change due to COVID-19).

This study aims to test the following hypotheses: first, in line with previous studies, after COVID-19, face-to-face consumption is expected to decrease, and online consumption is expected to increase. However, this may be influenced by factors such as age and gender. For example, the decline in eating out may be greater for men, and women may prefer to shop at supermarkets and drugstores close to their homes, than at department stores in the city center. The younger generation may be more digitally literate and choose to replace face-to-face consumption with online consumption. In addition to the government's promotion policy[8] and to avoid infection risk, cashless payments may become popular.

In contrast, purchase time hours in restaurants and pubs may decrease due to reduced face-to-face consumption, while purchase time hours at night may increase due to increased online consumption at home. In addition, the government's policy of cash transfers to households may have an impact on post-COVID consumption.

In this study, household structure (number of family members and number of children in the

Table 1. Descriptive statistics for sample data

VARIABLES	N	mean	sd	min	max
Age	21,360	49.37	9.643	25	73
Female	21,360	0.612	0.487	0	1
HouseholdIncome	21,360	3.734	1.707	1	9
FamilyNum	21,360	2.596	1.260	1	7
ChildNum	21,360	0.536	0.881	0	4
Expenditure	21,360	152,562	156,095	980	7.224×10^6
EC rate	21,360	0.0121	0.0413	0	0.710
Dining out rate	21,360	0.0574	0.0849	0	1
Entertainment rate	21,360	0.0408	0.0726	0	0.853
Transpotation rate	21,360	0.0181	0.0560	0	0.786
Housing & home rate	21,360	0.139	0.206	0	0.949
Supermarket rate	21,360	0.286	0.229	0	1
Department store rate	21,360	0.0108	0.0401	0	0.784
Drugstore rate	21,360	0.0595	0.0765	0	1
Cashless rate	21,360	0.662	0.295	0	1
MPurchase time	21,360	11.26	3.592	0	21.43

Note: Expenditures are in Japanese Yen.

family) is used as a proxy indicator for the impact of cash transfers on households to examine whether increasing family size affects consumption expenditure after COVID-19.

3. Result

3.1. Summary Statistics

Table 1 shows the results of descriptive statistics for the sample data. The average age and household income are almost the same as those of the Japanese consumers as a whole, however, regarding gender, the ratio of females is higher.

The average monthly consumption expenditure is approximately JPY 150,000, and the percentage of purchases made at supermarkets is approximately 28%. The sample also includes consumers who only use cash; however, the average percentage of cashless payments is about 60%, which is much higher when considering Japanese payments as a whole.

In the next subsection, the relationship between consumer attributes and consumption expenditure is explained based on the results of the regression analysis using panel data. In this study, because consumer attribute variables are time-invariant, we use a random effects model. First, to evaluate the effect of COVID-19 on the level of each indicator, we estimate the case in which only *aftercovid* is included as an explanatory variable. Next, to evaluate the effect of the attribute variables on the coefficients of each indicator, we estimate the case where the cross-terms (*aftercovid* multiplied by the attribute variables) are included in the explanatory variables.

3.2. Effect of COVID-19 on each indicator level

Table 2 shows the estimation results when only the COVID-19 dummy (*aftercovid*) is used as an explanatory variable in the regression.

First, the effect of the COVID-19 dummy was significant for all the indicators. It had a negative effect on overall consumption Expenditure, Dining out rate, Entertainment rate, Transportation rate, Department store rate, and the mean of purchase time (*MPpurchase*).

Conversely, it had a positive effect on the EC rate, Housing & home rate, Supermarket rate, Drugstore rate, and Cashless rate.

Age has a positive impact and gender has no significant impact on overall consumption expenditure. However, gender has a significant impact on individual consumption indicators. For example, female consumers spend a higher percentage of their spending on e-commerce, supermarkets, drugstores, and department stores, while male consumers spend a higher percentage of their spending on dining out, entertainment, and transportation. This may reflect gender roles in Japanese households.

The study obtained a positive relationship between household income level and overall consumption expenditure, dining out rate, department store rate, and cashless payment rate. The higher cashless payment rate for higher-income households may be related to the fact that higher-income households own and use more credit cards.

As for family structure, we found that the larger the family members, the lower the EC ratio and the higher the ratio of purchases at supermarkets and drugstores. This may mean that the larger the family size, the more likely they are to use physical stores rather than shop online.

3.3. Effect of COVID-19 on the estimated coefficients of attribute variables

Table 3 shows the estimation results when the cross-term between the COVID-19 dummy and the explanatory variable (*aftercovid* × attribute variable) are added as explanatory variables in the regression. The cross-term variables used here are as follows:

$covidage = aftercovid \times Age$

$covidfemale = aftercovid \times Female$

$covidHI = aftercovid \times HouseholdIncome$

$covidfamilyN = aftercovid \times FamilyNum$

$covidchildN = aftercovid \times ChildNum$

In Table 3, for many of the consumption indicators, the statistical significance of the *aftercovid* variable decreases, while the statistical significance of the cross-term between the *aftercovid* and the attribute variable increases[9]. This implies that the relationship between consumer attributes and consumption behavior changes before and during COVID-19.

The most striking result of the cross-term effect is the household income. Although household

Table 2. Result of panel data regression (random effect model) I

The dependent variable (consumption behavior index) is listed in each column of the table, and the explanatory variables (consumer attributes, Covid-19 dummy) are listed in each row of the table. Only *Aftercovid* is used as an explanatory variable in the regression.

VARIABLES	Expenditure	EC rate	Dining out rate	Entertainment rate	Transportation rate	Housing & home rate	Supermarket rate	Drugstore rate	Department store rate	Cashless rate	MPurchase time
aftercovid	−5,065***	0.00277***	−0.0161***	−0.00540***	−0.00854***	0.00306**	0.0242***	0.00411***	−0.00357***	0.0257***	−0.405***
	(1,720)	(0.000439)	(0.000722)	(0.000750)	(0.000628)	(0.00125)	(0.00137)	(0.000631)	(0.000437)	(0.00169)	(0.0239)
Age	1,187***	−0.000185*	−0.000354	−0.000100	0.000118	−0.00246***	0.00123*	-8.26×10^{-5}	0.000194**	2.44×10^{-5}	0.0210**
	(349.5)	(9.83×10^{-5})	(0.000228)	(0.000176)	(0.000122)	(0.000586)	(0.000642)	(0.000211)	(9.13×10^{-5})	(0.000892)	(0.0106)
female	−15,300*	0.00586***	−0.0240***	−0.0148***	−0.00554**	−0.0481***	0.0676***	0.0130***	0.00898***	−0.0205	0.532**
	(8,035)	(0.00226)	(0.00524)	(0.00405)	(0.00281)	(0.0135)	(0.0148)	(0.00485)	(0.00210)	(0.0205)	(0.245)
HouseholdIncome	8,045***	0.000529	0.00641***	0.00165*	−0.000695	−0.0116***	0.000782	−0.00205*	0.00201***	0.0259***	0.116**
	(1,774)	(0.000499)	(0.00116)	(0.000894)	(0.000620)	(0.00298)	(0.00326)	(0.00107)	(0.000463)	(0.00453)	(0.0540)
FamilyNum	−4,952	−0.00258***	−0.00168	−0.00268	−0.00143	−0.0332***	0.0294***	0.00650***	0.000887	−0.0257***	0.422***
	(3,533)	(0.000994)	(0.00231)	(0.00178)	(0.00123)	(0.00593)	(0.00649)	(0.00213)	(0.000923)	(0.00902)	(0.108)
ChildNum	3,497	−0.000457	−0.00113	0.00142	−0.00362**	0.00543	−0.00243	−0.00253	−0.00464***	0.00349	−0.576***
	(5,078)	(0.00143)	(0.00331)	(0.00256)	(0.00177)	(0.00852)	(0.00933)	(0.00306)	(0.00133)	(0.0130)	(0.155)
Jobdummy	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	130,713***	0.0168**	0.0950***	0.0697***	0.0243**	0.447***	−0.00238	0.0406**	−0.0114	0.641***	8.498***
	(27,943)	(0.00786)	(0.0182)	(0.0141)	(0.00976)	(0.0468)	(0.0513)	(0.0169)	(0.00730)	(0.0713)	(0.850)
Observations	21,360	21,360	21,360	21,360	21,360	21,360	21,360	21,360	21,360	21,360	21,360
Number of panelID	1,424	1,424	1,424	1,424	1,424	1,424	1,424	1,424	1,424	1,424	1,424

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3. Result of panel data regression (random effect model) II

The dependent variable (consumption behavior index) is listed in each column of the table, and the explanatory variables (consumer attributes, Covid-19 dummy) are listed in each row of the table. Cross-terms with *Aftercovid* and explanatory variables have been added as explanatory variables in the regression.

VARIABLES	Expenditure	EC rate	Dining out rate	Entertainment rate	Transportation rate	Housing & home rate	Supermarket rate	Drugstore rate	Department store rate	Cashless rate	MPurchase time
aftercovid	6,722	0.00420	−0.0212***	−0.00381	−0.0103**	0.0267***	0.0332***	−0.00327	−0.00252	0.0235**	−0.593***
	(11,825)	(0.00302)	(0.00496)	(0.00516)	(0.00431)	(0.00858)	(0.00941)	(0.00434)	(0.00300)	(0.0116)	(0.164)
Age	1,356***	−0.000168	−0.000466**	-9.48×10^{-5}	5.44×10^{-5}	−0.00221***	0.00141**	−0.000155	0.000169*	0.000180	0.0219**
	(376.2)	(0.000105)	(0.000235)	(0.000186)	(0.000132)	(0.000595)	(0.000652)	(0.000217)	(9.79×10^{-5})	(0.000902)	(0.0108)
covidage	−252.8	-2.53×10^{-5}	0.000168*	-8.15×10^{-6}	9.56×10^{-5}	−0.000372**	−0.000280*	0.000109	3.87×10^{-5}	−0.000233	−0.00139
	(208.7)	(5.33×10^{-5})	(8.76×10^{-5})	(9.10×10^{-5})	(7.62×10^{-5})	(0.000151)	(0.000166)	(7.66×10^{-5})	(5.30×10^{-5})	(0.000205)	(0.00290)
female	−18,430**	0.00467**	−0.0304***	−0.0153***	−0.00738**	−0.0445***	0.0617***	0.0148***	0.0114***	−0.0248	0.463*
	(8,454)	(0.00236)	(0.00536)	(0.00421)	(0.00297)	(0.0136)	(0.0149)	(0.00494)	(0.00220)	(0.0207)	(0.247)
covidfemale	4,695	0.00179*	0.00960***	0.000857	0.00276*	−0.00531*	0.00883***	−0.00264*	−0.00361***	0.00631	0.103*
	(3,941)	(0.00101)	(0.00165)	(0.00172)	(0.00144)	(0.00286)	(0.00314)	(0.00145)	(0.00100)	(0.00387)	(0.0547)
HouseholdIncome	9,431***	0.000231	0.00755***	0.00240**	0.000354	−0.0119***	−0.000521	−0.00185*	0.00236***	0.0239***	0.112**
	(1,912)	(0.000531)	(0.00120)	(0.000947)	(0.000672)	(0.00302)	(0.00331)	(0.00110)	(0.000497)	(0.00458)	(0.0549)
covidHI	−2,079*	0.000447	−0.00170***	−0.00112**	−0.00157***	0.000411	0.00196**	−0.000312	−0.000532*	0.00305***	0.00594
	(1,070)	(0.000273)	(0.000449)	(0.000466)	(0.000390)	(0.000776)	(0.000852)	(0.000392)	(0.000272)	(0.00105)	(0.0148)
FamilyNum	−6,646*	−0.00198*	−0.000563	−0.00346*	−0.00124	−0.0325***	0.0312***	0.00531**	0.000835	−0.0251***	0.380***
	(3,820)	(0.00106)	(0.00238)	(0.00189)	(0.00134)	(0.00602)	(0.00660)	(0.00220)	(0.000994)	(0.00913)	(0.109)
covidfamilyN	2,541	−0.000912	−0.00168*	0.00116	−0.000290	−0.000989	−0.00272	0.00178**	7.77×10^{-5}	−0.000796	0.0637**
	(2,179)	(0.000556)	(0.000914)	(0.000950)	(0.000795)	(0.00158)	(0.00173)	(0.000799)	(0.000553)	(0.00214)	(0.0302)
ChildNum	4,762	0.000266	−0.00310	0.00210	−0.00607***	0.00668	−0.00144	−0.00271	−0.00594***	0.00293	−0.583***
	(5,503)	(0.00153)	(0.00343)	(0.00272)	(0.00194)	(0.00866)	(0.00949)	(0.00316)	(0.00143)	(0.0131)	(0.157)
covidchildN	−1,897	−0.00109	0.00295**	−0.00102	0.00369***	−0.00187	−0.00149	0.000270	0.00195**	0.000833	0.0116
	(3,179)	(0.000811)	(0.00133)	(0.00139)	(0.00116)	(0.00231)	(0.00253)	(0.00117)	(0.000807)	(0.00312)	(0.0441)
Jobdummy	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	122,856***	0.0158*	0.0984***	0.0686***	0.0255**	0.431***	−0.00834	0.0455***	−0.0121	0.642***	8.624***
	(29,011)	(0.00811)	(0.0185)	(0.0145)	(0.0102)	(0.0472)	(0.0517)	(0.0171)	(0.00756)	(0.0717)	(0.857)
Observations	21,360	21,360	21,360	21,360	21,360	21,360	21,360	21,360	21,360	21,360	21,360
Number of panelID	1,424	1,424	1,424	1,424	1,424	1,424	1,424	1,424	1,424	1,424	1,424

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

income itself has a positive effect on overall consumption, the sign of the cross-term with the *aftercovid* dummy is negative and statistically significant. Similarly, for many other consumption indicators, the estimated signs are reversed for household income and its cross-term variable. This suggests that consumers with higher incomes are more likely to be suppressed in their consumption after COVID-19. There is a decrease in the consumption of expenditure items that involve face-to-face contact or travel, such as dining out, entertainment, transportation, and department stores, while spending on supermarkets near home increases. However, spending on e-commerce has not changed.

Therefore, it can be concluded that the higher the income, the higher the dependence on face-to-face consumption and the decrease in consumption is more attributable to the loss of consumption opportunities than to the decrease in income. In addition, the percentage of cashless payments increased among high-income households after the COVID-19 outbreak, but it is assumed that these consumers used credit cards at department stores rather than online stores.

The cross-term effect of gender is also significant in many cases. After the COVID-19 outbreak, women increased their purchases in EC and supermarkets, while they decreased their purchases in department stores, which can be interpreted as a shift from department stores in urban centers to EC and supermarkets around their homes.

For men, the COVID-19 caused a significant decrease in the dining out. The reversal of the sign of the gender cross-term for drugstores may suggest a change in the role of men with respect to shopping in the home.

The results for the cross-term effect on family size are statistically significant for a few items, but not for consumption in general. As for the number of family members, this may reflect the impact of the government's cash transfer policy and changes in the consumption behavior of single consumers.

3.4. Excluding the sample of declared state of emergency in 2020

The restrictions imposed on consumers and stores (especially restaurants and department stores) under the government's declaration of a state of emergency are thought to have led to a larger decrease in consumption. In particular, the first declaration of the state of emergency in 2020 (April and May) has a strong impact on consumption, so the estimation results in Table 3 may also be affected by this period.

Table 4 shows the results of the estimation excluding the sample during the declaration of the state of emergency in April and May 2020. The overall results are similar to that of Table 3. The *aftercovid* dummy variable demonstrates that the negative impact on dining out and positive impact on housing, home, and supermarkets remain unchanged. No significant changes were observed in the cross-term effects, but some of them lost their statistical significance. In

Table 4. Results of Panel Data Regression (Random Effects Model) III.

Each column of the table contains the dependent variable (consumption behavior index), and each row contains the explanatory variables (consumer attributes, Covid-19 dummy). Aftercovid and explanatory cross terms have been added as explanatory variables in the regressions. The estimation period excludes the declaration of the state of emergency (April and May 2020)

VARIABLES	Expenditure	EC rate	Dining out rate	Entertainment rate	Transportation rate	Housing & home rate	Supermarket rate	Drugstore rate	Department store rate	Cashless rate	MPurchase time
aftercovid	3,950	0.00470	−0.0174***	−0.000316	−0.00838*	0.0226**	0.0311***	−0.00423	−0.00357	0.0203*	−0.692***
	(12,574)	(0.00313)	(0.00521)	(0.00549)	(0.00457)	(0.00911)	(0.00952)	(0.00448)	(0.00324)	(0.0120)	(0.172)
Age	1,375***	−0.000166	−0.000454*	-8.87×10^{-5}	5.20×10^{-5}	−0.00222***	0.00141**	−0.000158	0.000168*	0.000188	0.0215**
	(386.3)	(0.000102)	(0.000243)	(0.000192)	(0.000136)	(0.000593)	(0.000646)	(0.000215)	(0.000101)	(0.000900)	(0.0108)
covidage	−145.5	-3.58×10^{-5}	0.000136	-1.54×10^{-5}	8.69×10^{-5}	−0.000275*	−0.000272	0.000113	6.34×10^{-5}	−0.000201	−0.00132
	(221.9)	(5.52×10^{-5})	(9.20×10^{-5})	(9.68×10^{-5})	(8.07×10^{-5})	(0.000161)	(0.000168)	(7.90×10^{-5})	(5.72×10^{-5})	(0.000212)	(0.00303)
female	−17,434**	0.00448*	−0.0302***	−0.0151***	−0.00731**	−0.0449***	0.0611***	0.0147***	0.0113***	−0.0249	0.458*
	(8,698)	(0.00231)	(0.00553)	(0.00433)	(0.00305)	(0.0136)	(0.0148)	(0.00490)	(0.00228)	(0.0206)	(0.247)
covidfemale	4,424	0.00157	0.00899***	−0.000236	0.00261*	−0.00537*	0.00585*	−0.00213	−0.00288***	0.00698*	0.129**
	(4,191)	(0.00104)	(0.00174)	(0.00183)	(0.00152)	(0.00303)	(0.00317)	(0.00149)	(0.00108)	(0.00401)	(0.0573)
HouseholdIncome	9,488***	0.000222	0.00757***	0.00233**	0.000359	−0.0118***	−0.000556	−0.00184*	0.00237***	0.0239***	0.114**
	(1,963)	(0.000520)	(0.00123)	(0.000973)	(0.000689)	(0.00301)	(0.00328)	(0.00109)	(0.000514)	(0.00457)	(0.0547)
covidHI	−1,478	0.000302	−0.00141***	−0.000895*	−0.00162***	0.000462	0.000932	−0.000474	−0.000280	0.00332***	0.00439
	(1,137)	(0.000283)	(0.000471)	(0.000496)	(0.000414)	(0.000824)	(0.000861)	(0.000405)	(0.000293)	(0.00109)	(0.0155)
FamilyNum	−6,741*	−0.00199*	−0.000528	−0.00341*	−0.00124	−0.0327***	0.0311***	0.00533**	0.000812	−0.0252***	0.379***
	(3,921)	(0.00104)	(0.00246)	(0.00194)	(0.00138)	(0.00600)	(0.00653)	(0.00218)	(0.00103)	(0.00911)	(0.109)
covidfamilyN	1,492	−0.000726	−0.00123	0.000574	−0.000495	−0.00123	−0.00258	0.00193**	−0.000156	−0.000186	0.0679**
	(2,317)	(0.000576)	(0.000960)	(0.00101)	(0.000842)	(0.00168)	(0.00175)	(0.000825)	(0.000597)	(0.00222)	(0.0317)
ChildNum	4,966	0.000273	−0.00301	0.00210	−0.00609***	0.00672	−0.00147	−0.00271	−0.00594***	0.00304	−0.584***
	(5,647)	(0.00149)	(0.00353)	(0.00280)	(0.00198)	(0.00862)	(0.00940)	(0.00313)	(0.00148)	(0.0131)	(0.157)
covidchildN	−994.3	−0.00137	0.00203	−0.000424	0.00368***	−0.00169	−0.00178	0.000351	0.00196**	−0.000161	0.0189
	(3,380)	(0.000840)	(0.00140)	(0.00147)	(0.00123)	(0.00245)	(0.00256)	(0.00120)	(0.000871)	(0.00324)	(0.0462)
Jobdummy	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	126,923***	0.0152*	0.0965***	0.0706***	0.0247**	0.431***	−0.00546	0.0453***	−0.0121	0.639***	8.675***
	(29,882)	(0.00794)	(0.0191)	(0.0149)	(0.0105)	(0.0470)	(0.0513)	(0.0169)	(0.00784)	(0.0715)	(0.855)
Observations	18,512	18,512	18,512	18,512	18,512	18,512	18,512	18,512	18,512	18,512	18,512
Number of panelID	1,424	1,424	1,424	1,424	1,424	1,424	1,424	1,424	1,424	1,424	1,424

Standard errors in parentheses
*** p < 0.01, ** p < 0.05, * p < 0.1

particular, the decreasing significance and reversal of sign of the gender cross-term effect in supermarkets, drugstores, and department stores may indicate a change in the roles of men and women in shopping.

The significance of the sign of total consumption expenditure and supermarkets and department stores disappeared for the cross-term with household income, suggesting that face-to-face consumption may have recovered due to the easing of restrictions on going out. Age and family structure (number of family members and number of children in the family) showed no significant changes. A slight decrease in the statistical significance of the cross-term variable for gender was observed.

4. Conclusion

The main conclusions of this study are as follows.

First, the COVID-19 pandemic had a significant impact on consumer behavior. Face-to-face consumption (eating out, travel, entertainment) has decreased significantly, and online consumption and the purchase of familiar daily necessities near home (shopping at supermarkets and drugstores) has increased. Also related to this point, there was a decrease in nighttime shopping and a trend toward earlier purchasing times. Furthermore, we found that cashless payments are on the rose.

Second, since the outbreak of the COVID-19, online consumption has been on the rise among single young women, and the gender gap in purchasing has been decreasing in supermarkets, drugstores, and department stores, where women used to be the main buyers.

Third, we found that consumption has decreased significantly with higher incomes after the COVID-19. Particularly for the dining out and transportation, there was no recovery trend even after the emergency ended. However, there was generally no significant relationship between family structure (number of family members, number of children in the family) and overall consumption. This may suggest that, for the recovery of consumption, it is important to ensure consumption opportunities, apart from measures such as monetary benefits.

These results are similar to the results of previous studies regarding the decline in face-to-face consumption, but we provide new findings regarding changes by store, purchasing time, the cashless payment, shopping behavior by gender, and consumption constraints by income group.

Finally, we discuss the limitations and future directions of this study. First, the sample data we used consists of relatively digitally well-informed consumers, which may be different from the average Japanese sample, thus presenting a sample data bias. Second, the study does not adequately consider the changes in consumer attributes, especially employment and infection insecurity. Since COVID-19, employment insecurity among non-regularly employed women, and infection insecurity among middle-aged and older consumers may have affected their consumption behavior. Third, we have not been able to analyze investment behavior in terms of finance to the extent we desired. In future studies, we intend to analyze changes in consumer behavior as well as financial behavior by extending the sample data over a longer period and adding the financial transaction data of consumers.

ACKNOWLEDGEMENTS

I would like to thank Professor Toshiki Jinushi (Kansai University) for his advice and comments at the meeting of the Japan Society of Monetary Economics, also thank the anonymous referees of JJMFE. This study was financially supported by JSPS KAKENHI Grant Number 19H01474 and edited by Editage for language and grammar.

NOTES

1. According to the latest labor force survey, the average number of workers in FY 2020 was 6.664 million, a decrease of 690,000 from the previous year. More than half of the workers (370,000) are in the accommodation and food services industry. In terms of the number of regular and non-regular workers, the number of female workers decreased by 650,000, whereas the number of male workers decreased by 320,000, suggesting that COVID-19 has had a significant impact on the employment of non-regular female workers, mainly those engaged in face-to-face services.
2. 1) At least 1,500 transactions were registered in 15 months (an average of 100 transactions per month), 2) there was a monthly record of purchases (at least one purchase), and 3) the monitors lived in the Tokyo metropolitan area. The reason for condition 3) is that the living environment of the monitors is considered to be similar, and the number of MHS registered monitors in other prefectures is relatively small, which increases the risk of identifying the monitors.
3. There are several caveats when using high-frequency purchase panel data. First, the correlation between the error terms in the daily purchase data is expected to be high, given the tendency to buy in bulk at the same store. Likewise, since there is a tendency to buy in bulk (hoarding home appliances and groceries) on weekends (work vacations), we use monthly aggregate data on consumption.
4. The MHS data is available by consumption item and by purchasing store. Of the 11 indicators listed below, the figures for the dining out rate, entertainment rate, transportation rate,

and housing and home rate, are based on the figures for the relevant indicators from the 15 major categories of consumption items. Data on other consumption items, such as clothing, education, and beauty, are also available.

The figures for the EC rate, Supermarket rate, Drugstore rate, and Department store rate are taken from the 55 major categories of purchasing stores. In addition, data on discount stores and home centers are also available. The C*ashless rate* and *MPurchase time* indices are calculated by the author based on data on the choice of payment method and the amount spent per hour by individual consumers.

5. Excluding payments for items such as taxes, utility bills, and insurance.
6. Household income (9-point scale, 1–9) is
   1 if the family annual income < 2 million yen
   2 if 2 million yen < annual income < 4 million yen
   3 if 4 million yen < annual income < 6 million yen
   4 if 6 million yen < annual income < 8 million yen
   5 if 8 million yen < annual income < 10 million yen
   6 if 10 million yen < annual income < 12 million yen
   7 if 12 million yen < annual income < 15 million yen
   8 if 15 million yen < annual income < 20 million yen
   9 if 20 million yen < annual income
7. The following 12 occupational classifications have been made:
   civil servant, manager/director, company employee (clerical), company employee (technical), company employee (other), self-employed, free business, housewife (housewife), part-time employees, student, other, unemployed.
8. From October 2019 to June 2020, the government implemented a campaign that allowed consumers to earn up to 5% back when paying cashless payments.
9. For dining out rate and transportation ratio, the effect of the *aftercovid* dummy is still significantly negative.

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