

How Much Did People Refrain from Service Consumption due to the Outbreak of COVID-19?

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How Much Did People Refrain from Service Consumption due to the Outbreak of COVID-19?

Tsutomu Watanabe* Yuki Omori†

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Abstract

With the spread of coronavirus infections, there has been a growing tendency to refrain from consuming services such as eating out that involve contact with people. Self-restraint in service consumption is essential to stop the spread of infections, and the national government as well as local governments such as the Tokyo government are calling for consumers as well as firms providing such services to exercise self-restraint. One way to measure the degree of self-restraint has been to look at changes in the flow of people using smart phone location data. As a more direct approach, this note uses credit card transaction data on service spending to examine the degree to which people exercise self-restraint. The results indicate that of men aged 35-39 living in the Tokyo metropolitan area, the share that used their credit card to pay for eating out in March 2020 was 27 percent. Using transaction data for January, i.e., before the full outbreak of the virus in Japan, yields an estimated share of 32 percent for March. This means that the number of people eating out fell by 15 percent. Apart from eating out, similar self-restraint effects can be observed in various other sectors such as entertainment, travel, and accommodation. Looking at the degree of self-restraint by age shows that the self-restraint effect was relatively large among those in their late 30s to early 50s. However, below that age bracket, the younger the age group, the smaller was the self-restraint effect. Moreover, the self-restraint effect was also small among those aged 55 and above. Further, the degree of self-restraint varies depending on the type of service; it is highest with regard to entertainment, travel, and accommodation. The number of people who spent on these services in March 2020 was about half of the number during normal times. However, the 80 percent reduction demanded by the government has not been achieved.

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1 Introduction

With the spread of coronavirus infections, there has been a growing tendency to refrain from consuming services such as eating out that involve contact with people. Self-restraint in service consumption is essential to stop the spread of infections, and the national government as well as local governments such as the Tokyo government are calling for consumers as well as firms providing such services to exercise self-restraint.

Specifically, Prime Minister Shinzo Abe declared a one-month long state of emergency in Tokyo and six other prefectures on April 7, 2020 and expanded it to the entire country on April 16. PM Abe stated in his speech on April 7 that “According to an estimate by the experts, if all of us make efforts and reduce opportunities for person-to-person contact by a minimum of 70 percent, or ideally 80 percent, we will cause the increase in the number of patients to reach its peak two weeks from now and shift over into a decrease. . . . I ask people to refrain from going out, aiming at a 70 to 80 percent decrease, for the limited period of one month between now and the end of Golden Week holidays on May 6.”¹

The purpose of this note is to measure the degree to which people in Japan have been exercising self-restraint since the outbreak of COVID-19. One way to do so is to look at changes in the flow of people using mobile phone location data.² As a more direct approach, we use credit card transaction data on service spending to examine the degree to which people exercise self-restraint.

2 Credit card transaction data

2.1 Sales and purchase record data

Data to measure consumer spending includes sales data and purchase data. Sales data is information generated by the seller (a store or firm), while purchase data is information generated by the buyer (consumer). A typical example of the former is point of sale (POS) data, which records information on the seller side such as how many items of a product manufactured by which firm were sold at which shop on which day. A typical example of the

¹PM Abe’s speeches on April 7 and April 16 are available at: https://japan.kantei.go.jp/98_abe/statement/202004/_00001.html; https://japan.kantei.go.jp/98_abe/statement/202004/_00002.html

²For example, mobile phone location data covering 78 million users provided by DOCOMO InsightMarketing, Inc., is used to obtain high frequency estimates of the number of people staying or not staying at home during the daytime for pixels with a size of 500m × 500m. See T. Mizuno, T. Ohnishi, and T. Watanabe, “Estimates of the extent to which people are staying at home during the daytime using mobile phone data. Online: https://www.canon-igs.org/column/macroeconomics/20200422_6369.html

latter is credit card transaction data, which records information on the buyer side such as how much a consumer spent at which store on which day.

If the aim is to measure the total amount of household consumption, that is, private consumption, it does not matter which of the two types of data is used. We can measure private consumption by adding up the sales data of all stores in Japan. Similarly, we can measure private consumption by adding up all the consumption spending of individual households.³ Since the amount of purchases and the amount of sales are identical, the result in principle is the same regardless of which type of data is used.⁴

However, sales and purchase data can be used not only for measuring personal consumption, and in other uses, the particularities of each type of data emerge. For example, POS data includes information on the price at which a certain product was sold on a certain day. On the other hand, credit card transaction data, which is a prime example of purchase data, usually does not contain price information about individual purchases.⁵ On the other hand, since credit card transaction data records who made purchases, it is suitable for investigating the relationship between consumers' characteristics and their purchase decisions.

2.2 Differences among individuals in their reaction to the “corona shock”

If we want to examine how much private consumption in Japan has fallen as a result of the corona shock, we can also use either sales or purchase data.⁶ However, if we want to know

³The central bank of the United States, the Federal Reserve, is thinking about constructing personal consumption statistics using credit and debit card transaction data. For details, see Aditya Aladangady et al., “From Transactions Data to Economic Statistics: Constructing Real-Time, High-Frequency, Geographic Measures of Consumer Spending,” *Big Data for 21st Century Economic Statistics*, University of Chicago Press, 2019. Online: <https://www.nber.org/chapters/c14267.pdf>.

⁴In practice, there are a number of conceptual differences between the two types of data, so that the results will differ depending on which type of data are added up. For example, the sales data of stores in Japan includes sales to foreign tourists, so that the sum of all sales data is the total consumption of residents in Japan and foreign tourists. In contrast, the sum of the purchase data of residents in Japan represents only the total consumption of residents in Japan, so that sum totals of the sales and purchase data do not match. For details on the differences between sales and purchase data, see, for example, the Bank of Japan Research Paper on “The Consumption Activity Index,” (May 2016). Online: https://www.boj.or.jp/en/research/brp/ron_2016/data/ron160502a.pdf.

⁵Another type of purchase data is home scanner data, which does include price information. Home scanner data is used by market research firms that enter a monitoring contract with individual consumers to track their purchases in a digital household account book. Such household account books contain information such as products bought, the quantity, and price at the time of purchase. However, the number of consumers that market research firms can ask to act as monitors is limited and at most consists of several tens of thousands of individuals.

⁶For details on the response of prices to the corona shock, see Tsutomu Watanabe, “The Responses of Consumption and Prices in Japan to the COVID-19 Crisis and the Tohoku Earthquake,” CJEJ Working Papers No. 373, Columbia Business School, March 2020. Online: <https://voxeu.org/article/responses-consumption-and-prices-japan-covid-19-crisis-and-tohoku-earthquake>, VOX CEPR Policy Portal, 04 April 2020.

how people with certain characteristics responded to government messages such as requests for self-restraint as well as developments in the spread of the coronavirus, purchase data is more suitable. For example, it has been suggested that seniors are less likely to comply with the government’s request for self-restraint than younger people,⁷ so if we want to dig deeper into differences in behavior across individuals and the reasons for those differences based on actual expenditure data (and not through indirect methods such as questionnaire surveys and people’s movements), credit card transaction data is indispensable.

Credit card transaction data from “JCB Consumption NOW” provided by Nowcast, in addition to information on trends in personal consumption and consumption by industry in Japan overall, also provides information on consumption categorized in terms of individuals’ characteristics. Such information is provided on the premise that measures are taken to maintain confidentiality by making it impossible to identify individuals, so that the day-to-day purchasing behavior of individuals cannot be traced. However, consumers are grouped by gender, age, and region, and information is provided about, for example, how much each group spent on eating out and entertainment, and how consumers differ in their characteristics. In the following, we will explain how we measure people’s response to the coronavirus pandemic, and in particular, the degree of self-restraint with regard to expenditure on services such as eating out and entertainment, using this spending data categorized in term of individuals’ characteristics.

3 Measurement of self-restraint with regard to service consumption

3.1 Soft and hard self-restraint

Imagine the following. If an individual is afraid of being infected with the novel coronavirus, they may decide to change their behavior for example with regard to eating out and reduce the number of restaurant visits; alternatively, they may not change the number of visits but finish earlier than usual. In either case, the monthly spending on eating out would be lower than usual, but not zero. On the other hand, in the case of extreme self-restraint, where an individual stops going to restaurants altogether, the individual’s monthly spending on eating out would be zero.

⁷These arguments are based on questionnaire surveys and data on people’s movements. See, for example, <https://www.itmedia.co.jp/business/articles/2004/03/news098.html> and <https://tech-blog.rei-frontier.jp/entry/2020/04/01/204833> (both in Japanese).

Since individuals cannot be identified, we cannot fully observe for individuals whether they engage in the former type of soft self-restraint or the latter type of hard self-restraint. However, we can extract information about soft self-restraint and hard self-restraint simply by looking at the aggregate values for groups with the same characteristics as a particular individual. In the data, soft restraint will appear in the form that, in a group of credit card users with the same characteristics as that individual, the average per capita spending on eating out of those that did use their credit card to pay for eating out will have decreased in that month, even if only a little. On the other hand, hard restraint will appear in the data in the form that the share of those that spent on eating out among that group declined in that month. It is important to note that neither piece of information identifies an individual.

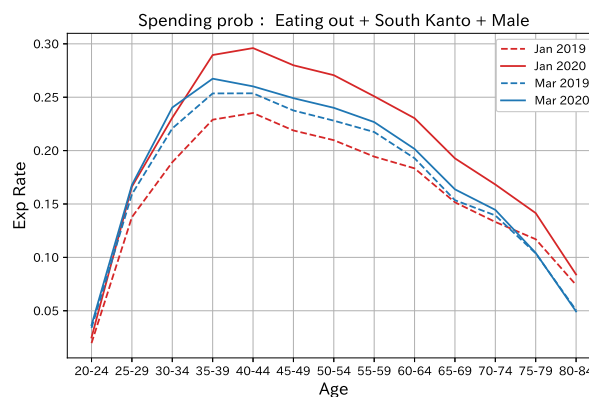
Distinguishing between soft and hard self-restraint in this manner, we can separate the degree of self-restraint into the change in the average spending of those who spent on eating out and the change in the share of those who spent on eating out in the first place. In economics, the former is called the intensive margin, while the latter is called the extensive margin.⁸ Below, we will focus on the extensive margin to examine the link between individuals' characteristics and the extent to which they exercise self-restraint.

The first reason for focusing on the extensive margin is that the results of the actual decomposition of changes in spending into the extensive and intensive margins using the "JCB Consumption NOW" data show that most of the decline in spending on services since the corona shock is explained by the extensive margin.⁹ Second, the current goal of the national government and local governments such as the Tokyo Metropolitan Government is to reduce contact among people by 80 percent, and for that reason they are demanding to refrain from eating out. Although the details of the self-restraint requested by the national and local governments are not always clearly defined, it is probably impossible to achieve the

⁸Extensive margin and intensive margin are widely used concepts in economics. For example, POS data on the sales of a particular store on a particular day are the product of the number of customers visiting the store and the amount of purchases per customer. The number of customers visiting the store is the extensive margin, while the amount of purchases per customer is the intensive margin. Moreover, the turnover of a firm in a particular month is the product of the number of successful transactions of that firm and the amount per transaction. The former is the extensive margin, the latter the intensive margin. Or taking yet another example, the value of a country's exports in a particular month is the product of the number of countries to which the country exports and the average value of exports per country to which the country exports. The former is the extensive margin and the latter the intensive margin. Similarly, when measuring labor input, the extensive margin refers to how many people are working and the intensive margin to how many hours one person works on average.

⁹For details, see Tsutomu Watanabe "Decomposition of Credit Card Expenditure into the Expenditure per Person and the Number of Persons Spending," March 29, 2020. Online: https://s3-ap-northeast-1.amazonaws.com/jcbconsumptionnow.com/News/20200401_Nowcast_Watanabe.pdf

Figure 1: Share of card users eating out



Note: The vertical axis shows the share of men living in South Kanto (Tokyo, Kanagawa, Chiba, and Saitama prefectures) who used their credit card to pay for eating out in a given month.

goal of reducing contact among people by 70-80 percent through soft restraint such as eating out but keeping it short. Thus, to examine whether consumers are responding sufficiently to the self-restraint requests of the national and local governments it is appropriate to look at the extensive rather than the intensive margin.

3.2 Share of card users using their card to pay for services: The “spending probability”

We start by explaining how we measure the degree of hard self-restraint by taking eating out as an example. Figure 1 shows the result of calculating the share of card users that used their card to pay for eating out. The figures are for men living in the South Kanto region (Tokyo, Kanagawa, Chiba, and Saitama prefectures). The blue line in the figure shows the shares in March 2020, with the horizontal axis showing the age group and the vertical axis showing the percentage share. For example, the value corresponding to the 35-39 age range is 0.267, indicating that 26.7 percent of men living in the South Kanto region falling into this age range used their credit card to pay for eating out in March 2020.¹⁰ Below, we will call the share of card users that used their card to pay for a service such as eating out the “spending probability.”

¹⁰To be precise, we use a data set of about 1 million active JCB members to calculate the shares (“spending probabilities”). In the data set, there were about 18,000 men aged 35-39 living in the South Kanto region, of which 26.7% in March 2020 used their JCB card to pay for eating out.

The red line in the figure shows the spending probability for January 2020. Since January 2020 is before the outbreak of the corona shock, the difference between the blue line and the red line shows how much spending has been suppressed. For example, in the age group of 35-39 year-olds, the spending probability in January 2020 was 28.9 percent, so the difference of 2.2 percentage points in March 2020 represents the self-restraint effect. However, this calculation is not accurate. The reason is that spending on eating out is seasonal, and we have not considered this factor. In fact, looking at the spending probability a year earlier in March and January 2019 (shown by the broken lines in the figure), the spending probabilities for this age group were 25.4 percent and 22.9 percent, respectively, meaning that the share of those using their card to pay for eating out in March was 2.5 percentage points higher than in January. This suggests that March is a month in which eating out increases, maybe because this is the end of the academic and fiscal year.

A method often used to eliminate seasonal fluctuations is a comparison with the same period of the previous year. In this example, this would correspond to comparing the spending probability for March 2020 and the spending probability for March 2019. The spending probability for March 2020 is 1.3 percentage points higher than that for March 2019. If we take these figures at face value, they imply that there has been no self-restraint, since the share is higher than that a year earlier. However, this interpretation would also not be appropriate. The reason is that the probability for March 2020 includes the effect of the reward point system that the government introduced in October 2019 in order to facilitate non-cash payments. Since consumers receive points when paying by credit card, they are more likely to pay by credit card instead of cash, so that the difference between March 2020 and March 2019 reflects this effect as well.

3.3 Estimation of the self-restraint effect

The above considerations can be summarized as follows. Denoting the probability of spending on eating out among 35-39 year-olds in March 2020 by $\Pr(\text{Spending on eating out in March 2020})$, this spending probability is the sum of the following three effects: the effect of the reward point system, the effect of self-restraint, and the seasonal factor for March. This can be written as

$$\begin{aligned} \Pr(\text{Spending in Mar 2020}) \\ = \text{Point reward effect} + \text{Self-restraint effect} + \text{March seasonal factor} \quad (1) \end{aligned}$$

Figure 2: Estimation of the self-restraint effect with regard to eating out



Note: The blue line represents the estimated self-restraint effect using equation (6). The green line estimates the difference between the seasonal factors for January and March using the spending probabilities for January and March for four years (2016 to 2019).

Similarly, the spending probabilities for January 2020, March 2019, and January 2019 can be expressed as follows:

$$\Pr(\text{Spending in Jan 2020}) = \text{Point reward effect} + \text{March seasonal factor} \quad (2)$$

$$\Pr(\text{Spending in Mar 2019}) = \text{March seasonal factor} \quad (3)$$

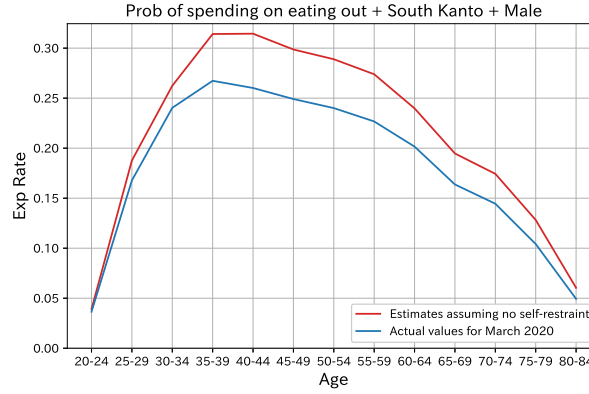
$$\Pr(\text{Spending in Jan 2019}) = \text{January seasonal factor} \quad (4)$$

While the above is a simplification of the way that the spending probability in each month is determined, it illustrates the point that the spending probabilities for March and January 2019 were determined only by seasonality. In March and January 2019, there were no major events comparable to the corona shock or the point reward system. That said, it cannot be ruled out that the probabilities for these months maybe have been affected by some other event, even if only a minor one. Equations (3) and (4) imply that no such event occurred. We will return to this point when presenting our estimations.

Given the spending probability for each month represented by equations (1) to (4), the self-restraint effect can be extracted as follows. First, subtracting equation (2) from equation (1) yields

$$\begin{aligned} & \Pr(\text{Spending in Mar 2020}) - \Pr(\text{Spending in Jan 2020}) \\ &= \text{Self-restraint effect} + \text{March seasonal factor} - \text{January seasonal factor} \end{aligned} \quad (5)$$

Figure 3: The share of people spending on eating out: Comparison with the case with no self-restraint



Note: The estimates without the self-restraint effect are obtained using equation (7).

The spending probabilities for March and January 2020 were both affected by the point reward system, but the effect of the point reward system disappears by taking the difference. On the other hand, the self-restraint effect remains, because this effect only applies in March 2020. However, the March and January seasonal factors are still included and need to be removed. In order to remove the seasonal factors, equation (4) should be subtracted from equation (3), and the result should be subtracted from equation (5). The calculation is as follows:

$$\begin{aligned}
 & [\text{Pr}(\text{Spending in Mar 2020}) - \text{Pr}(\text{Spending in Jan 2020})] \\
 & - [\text{Pr}(\text{Spending in Mar 2019}) - \text{Pr}(\text{Spending in Jan 2019})] \\
 & = \text{Self-restraint effect}
 \end{aligned} \tag{6}$$

The blue line in Figure 2 shows the results of estimating the self-restraint effect using equation (6). Looking at the age group of 35-39 year-olds, the self-restraint effect is 4.7 percentage points, which is larger than when we simply subtract the value for January 2020 from that for March 2020 (2.5 percentage points). Looking at other age groups, the self-restraint effect is largest for 40-44 year-olds (5.4 percentage points). The effect becomes smaller the younger the age group and for those aged 20-24 is only 0.3 percentage points. Moreover, although not to the same extent as for younger age groups, the self-restraint effect also becomes smaller the older the age group for those above 40-44 years old.

In equation (6), the difference between the seasonal factors for March and January (March seasonal factor - January seasonal factor) is calculated using the difference in spending probabilities between March and January 2019. However, as mentioned earlier, the difference in spending probabilities between March and January 2019 may include factors other than seasonal factors. Therefore, using data for the four years from 2016 to 2019, we also calculated the difference between the spending probabilities for March and January for each year and used the average as the difference in the seasonal factors to repeat the estimation. While the difference between the March and January values for each year may include factors other than seasonal factors, taking the average of the four years means that differences other than seasonal factors should more or less cancel each other out. The green line in Figure 2 shows the estimates of the self-restraint effect obtained using this approach. While the blue and green lines differ slightly different for those aged 70 and above, for the other age groups the values are almost identical. Moreover, the result that the self-restraint effect is largest among those aged 40-44 remains unchanged.

Next, in Figure 3, we estimated the spending probability assuming that there was no self-restraint by subtracting the self-restraint effect from the actual spending probability in March 2020. In other words, the spending probability without self-restraint is calculated as follows:

$$\begin{aligned}
& \Pr(\text{Spending in Mar 2020}) - [\Pr(\text{Spending in Mar 2020}) - \Pr(\text{Spending in Jan 2020})] \\
& + [\Pr(\text{Spending in Mar 2019}) - \Pr(\text{Spending in Jan 2019})] \\
& = \Pr(\text{Spending in Jan 2020}) + \Pr(\text{Spending in Mar 2019}) - \Pr(\text{Spending in Jan 2019})
\end{aligned} \tag{7}$$

The figure indicates that in the age group of 35-39 year-olds, for example, the actual spending probability in March 2020 was 26.7 percent, but without self-control, that is, if people had continued eating out as usual, the spending probability would have been 31.4 percent. The decrease in the spending probability from 31.4 percent to 26.7 percent means that the number of people going out to eat out has decreased by about 15 percent for this age group. Even among 40-44 year-olds, the age group showing the greatest self-restraint, the spending probability decreased only from 31.4 percent to 26.0 percent, meaning that compared to the hypothetical case with no self-restraint, the number of people eating out decreased only by 17 percent. These figures are far below the reduction by 80 percent requested by the national and Tokyo governments. While the values calculated here are based on the “JCB consumption NOW” data for March 2020 and therefore do not reflect the effect of full-scale

self-restraint requests from the government since April, they suggest that to achieve the intended reduction of 80 percent further changes in consumers' mindset are necessary.

4 Estimation results

While the analysis in the previous section focused on eating out, we also conducted similar calculations for various other service industries. Figure 4 shows the spending probabilities, Figure 5 shows the estimated self-restraint effect, and Figure 6 shows the comparison with the case without self-restraint.

Figure 5 shows¹¹ that the self-restraint effects with regard to entertainment and transportation were almost the same as those with regard to eating out. A certain amount of self-restraint can also be observed with regard to accommodation and travel. On the other hand, with regard to coffee shops and golf courses the self-restraint effect was small. Meanwhile, the effect of self-restraint with regard to *izakaya* (Japanese-style bars that also serve food), while not zero, was very limited.¹²

Looking at the degree of self-restraint by age group, Figure 5 further shows that for transportation, entertainment, accommodation, etc., this follows a U-shape, like for eating out.¹³ That is, the self-restraint effect is relatively large among those aged 35 to 54, but among those under 35, it becomes weaker the younger the age group. At the same time, the self-restraint effect is also weak among those aged 55 and above. In particular, the weakness of the self-restraint effect among seniors with regard to entertainment is remarkable, and self-restraint is in fact weaker than among the young. For example, while the self-restraint effect with regard to entertainment is 4 percentage points among 25-29 year-olds, it is about the same level for 65-69 and 70-74 year-olds and is less than 4 percentage points for older age groups.

Next, Figure 6, which compares the results with the case without self-restraint, shows that the spending probabilities for travel, accommodation, and entertainment decreased sub-

¹¹The blue line in Figure 5 shows estimates of the self-restraint effect using equation (6), while the green line shows the self-restraint estimates using not only the values for 2019 but those for the past four years (2016 to 2019) to remove seasonal factors. Both lines show almost the same pattern. The discussion in the text is based on the results depicted by blue line.

¹²The self-restraint effect with regard to communication and content delivery is not negative but positive. This shows that the spending probability for these industries in March 2020 (the estimate obtained after the various adjustments described in the previous section) was high. This indicates that the probability of spending on these services increased since they act as substitutes for services provided through contact with people.

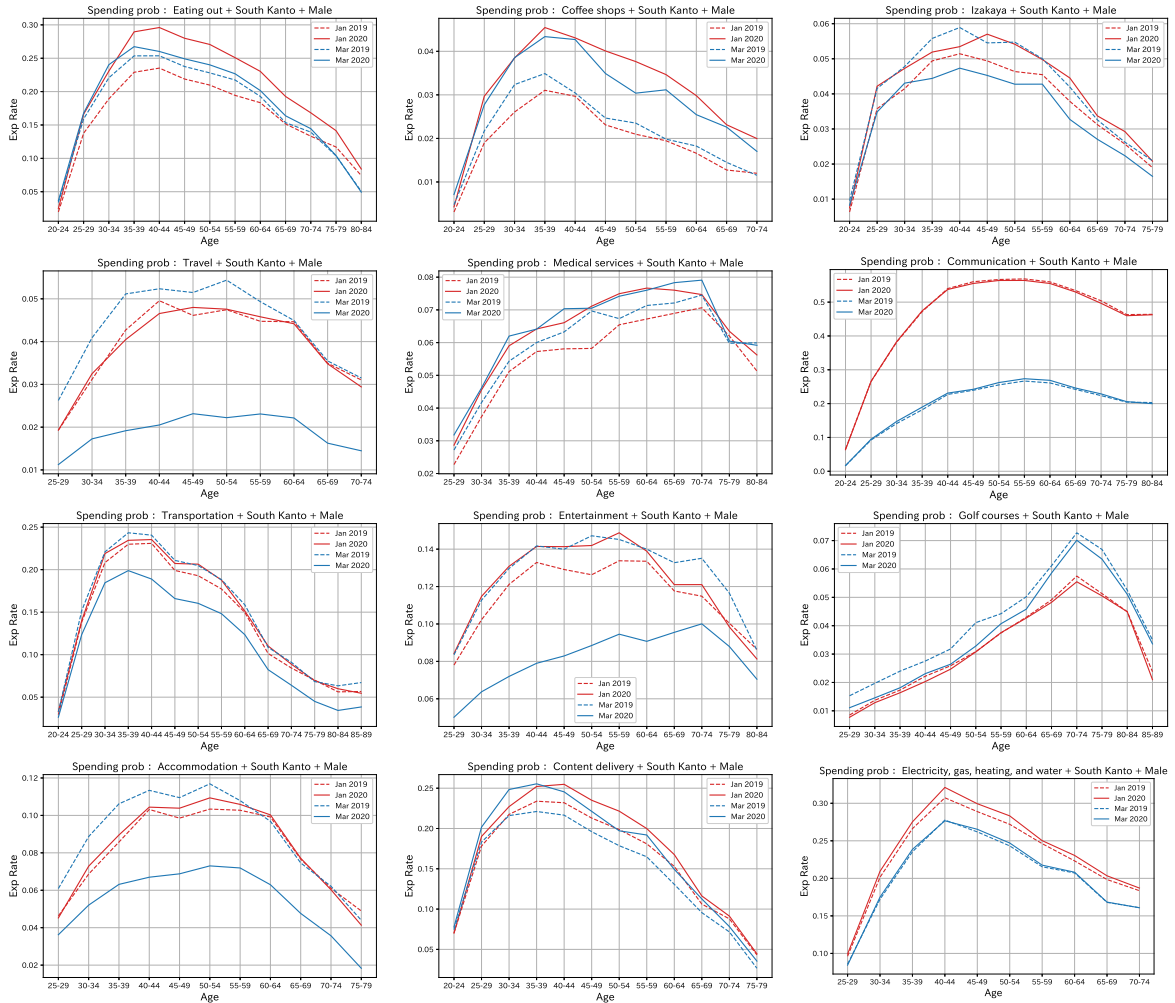
¹³The pattern for travel is somewhat different in that the self-restraint effect is very similar for all age groups.

stantially. Looking at the age group of 50-54 year-olds, the actual value for travel in March 2020 is 2.2 percent, while the estimate assuming that there was no self-restraint is 5.4 percent. In other words, under normal circumstances 5.4 percent of credit card users in this age group would have spent on travel, but the actual share was only 2.2 percent, indicating that 59 percent of people refrained from traveling. As for entertainment, the actual value for 50-54 year-olds in March 2020 was 8.8 percent, which is a decrease of 46 percent compared with the share of those normally spending on entertainment (16.3 percent). Thus, about half of the people who normally spend at least to some extent on these services did not spend any money on them at all, suggesting that they actively refrained from going out. However, even with regard to these services, the degree of self-restraint was only around 50 percent and did not reach the 80 percent demanded by the government.

Figures 4 to 6 are all calculated for male residents of the South Kanto region. In order to examine how the self-restraint effect differs across regions, Figure 7 shows the estimation results for the self-restraint effect with regard to eating out for men aged 35-64 by prefecture. First, looking at the actual values for March 2020, the ratio of those who spent on eating out in Tokyo, which has the highest share (spending probability) with 27.5 percent, was four times as large as that in Fukushima, which with 6.5 percent has the lowest share. This shows that the share of people who spend on eating out differs greatly across prefectures. In contrast, the estimates of the self-restraint effect represented by the bars do not differ that much across prefectures.¹⁴ For example, the self-restraint effect in Tokyo is 5.6 percentage points, while in Fukushima it is 2.5 percentage points, indicating that the difference in the self-restraint effect is not as large as that in spending probabilities. These results suggest that the extent to which people refrained from eating out was not substantially affected by the number of infected persons in the area and differences in efforts by local governments.

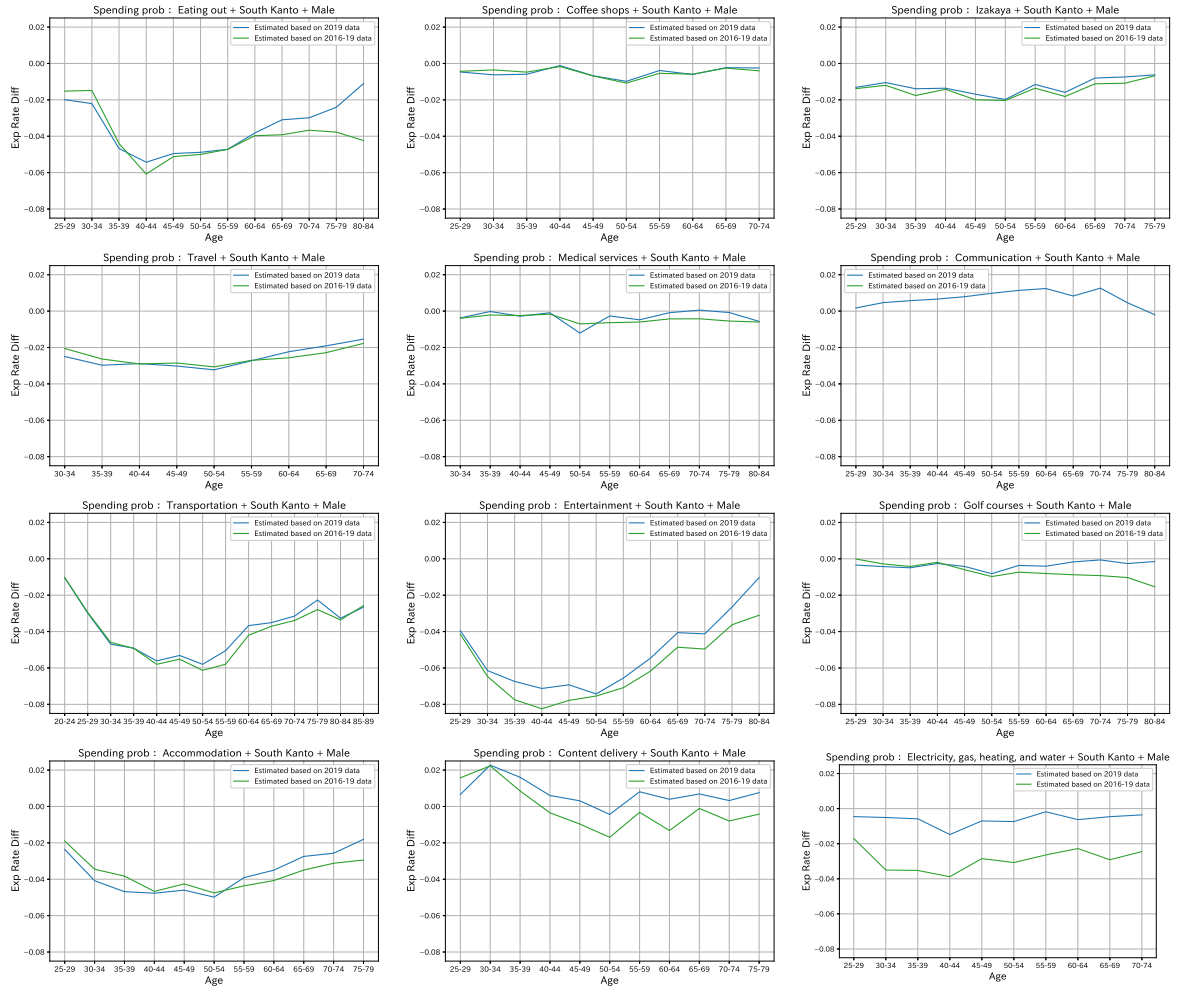
¹⁴That said, for Nagano, Shiga, and Kumamoto, the estimated self-restraint effect is almost zero, thus showing a clearly different pattern from other prefectures.

Figure 4: Probability of spending on services



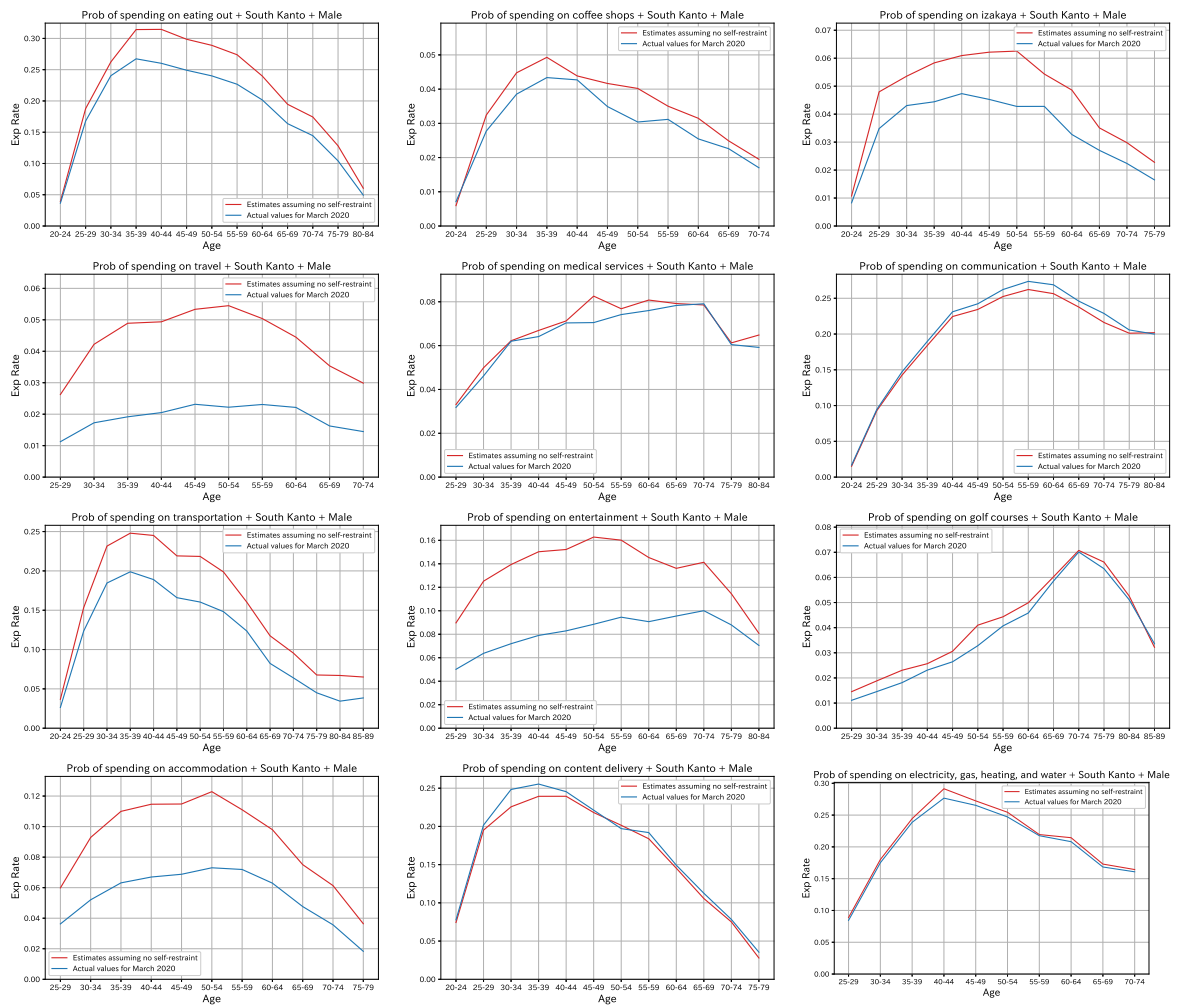
Note: The vertical axis of each graph shows the percentage of men living in South Kanto (Tokyo, Kanagawa, Chiba, Saitama) that used their credit card to pay for each type of services. “Communication” includes internet service providers and mobile telephony; “Transportation” includes train, bus, taxi, and airplane; “Entertainment” includes cinemas, sports facilities, and amusement parks; “Accommodation” includes hotels and Japanese-style inns. For details on how the original data used for the figure can be accessed, please contact Nowcast (info@nowcast.co.jp).

Figure 5: Estimation results of the self-restraint effect with regard to services



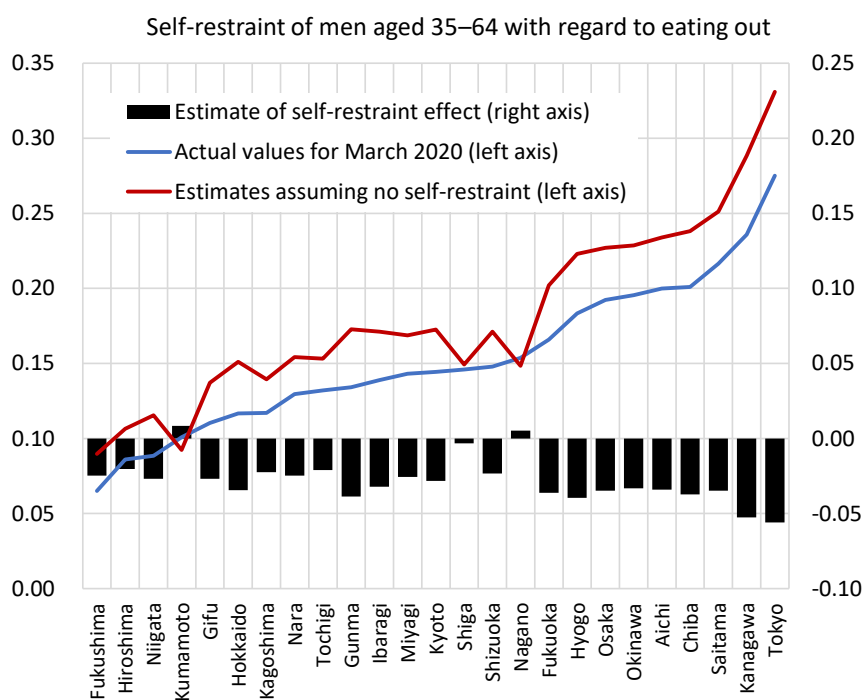
Note: The blue line shows estimates of the self-restraint effect using equation (6). The green line shows the self-restraint estimates using the January and March spending probabilities not for a single year but those for four years (2016 to 2019) when estimating the difference in the seasonal factor for January and March. “Communication” includes internet service providers and mobile telephony; “Transportation” includes train, bus, taxi, and airplane; “Entertainment” includes cinemas, sports facilities, and amusement parks; “Accommodation” includes hotels and Japanese-style inns. For details on how the original data used for the figure can be accessed, please contact Nowcast (info@nowcast.co.jp).

Figure 6: Comparison with the case assuming no self-restraint



Note: The estimates for the case assuming no self-restraint are calculated using equation (7). For details on how the original data used for the figure can be accessed, please contact Nowcast (info@nowcast.co.jp).

Figure 7: Self-restraint with regard to eating out by prefecture



Note: The figure shows the estimates for men aged 35–64 in each prefecture. For prefectures not shown in the figure we could not calculate the self-restraint effect because the number of observations was too small. For details on how the original data used for the figure can be accessed, please contact Nowcast (info@nowcast.co.jp).