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Economic Analysis based on the Mobile Phone GPS Data and Monitoring Consumer Behavior During the COVID-19 Pandemic

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Abstract

In order to understand what is happening in the underlying economy, it is useful to gain a picture of what people are doing. When people go out, they may do so in order to engage in some kind of economic activity. In this research, we measured the level of economic activity by gaining a macro picture of people's movements. Specifically, we used the location data (GPS data) of mobile phones owned by the customers of major Japanese mobile carrier au to measure changes in the movements of people in key urban areas, and to show the relationship between these changes and macroeconomic variables. Our results found a notable correlation between the number of visitors to city areas and GDP consumer spending and spending-related statistics. Furthermore, we found that the people's movements especially have a strong correlation with the consumption data of services. In addition, we found that there is an inverse correlation between online spending and the people's movements. In Japan, the spread of COVID-19 has had a marked impact on people's activity in 2020. This negative correlation indicates that a change in people's behavior while COVID-19 continues to spread, in the form of staying at home more, led to an increase in online shopping.

Keywords: Mobile Phone GPS Data, Big Data, Economic Activity, Consumer Spending, COVID-19

1 Introduction

In recent years, various types of data are being used in economic analysis to complement government economic statistics. These data, called alternative data, include high-frequency sales data and logistics data, big data that captures various economic activities, and unstructured data such as images and text data that reflect economic activities. The advantage of using alternative data is not only the richness of the information, but also the quickness of the information. For example, in order to grasp economic changes quickly, consumption data based on credit card payment data, point-of-sale (POS) data at retail stores, and various business data are used in an integrated manner [1]. The economic analysis using the alternative data have been conducted to estimate economic trends in real time and with high accuracy.

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For example, [2, 3] show the possibility of using Google search data for economic prediction. Additionally, web search data is helpful in forecasting consumer behavior [4] and even financial market activity [5–7]. A similar methodology has been applied to social media such as Twitter. The indices based on the Twitter data is useful to predict economic activity [8, 9] and stock market activity [10]. In addition, night-time light and remote sensing data are widely used to measure economic activity [11–14]. High-frequency electricity data is also useful for the estimation of economic activity [15]. Furthermore, [16, 17] track employment shocks using mobile phone call records. [18] propose a data-driven analytical framework to monitor socio-economic activity using mobility features extracted from mobile phone data. As we mentioned, these have already become indispensable approaches to economic analysis.

2 Mobile Phone GPS Data for Economic Analysis

In order to understand what is happening in the underlying economy it is useful to be able to gain a picture of what people are doing. For example, when people go out and about on the weekend, it is possible that they do so in order to undertake some kind of economic activity. Gaining a macro snapshot of people's movements thus makes it possible to gauge the level of economic activity. The location data of people's mobile phones can be useful in this context [19] [20].

In this study, we focus on the behavioral patterns of people during COVID-19 pandemic. In order to understand the change of the people's behavior pattern, the location data of the people's mobile phones can be useful. In this research, we use the location data (GPS data) of mobile phones owned by the customers of major Japanese mobile phone company au to measure changes in the number of people in key areas, and use the findings suggested by these changes to create macroeconomic data points. In this research, we use the location data which is provided by KDDI Location Analyzer, consisting of anonymized GPS data of mobile phones owned by au customers via user agreements. The data does not include the users' data of roaming services by overseas visitors to Japan.

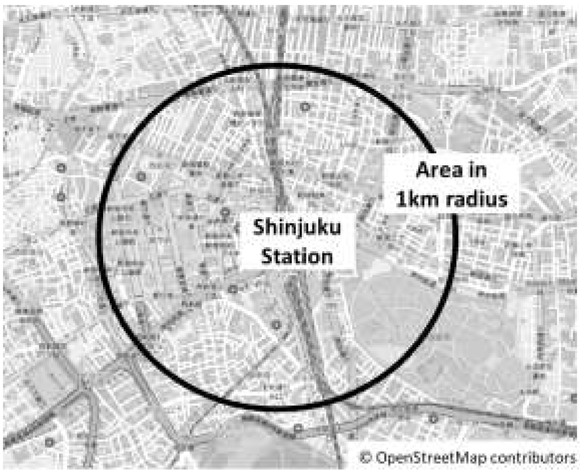

Figure 1: Map showing area in a 1km radius from Shinjuku Station

Specifically, based on the GPS data of people's mobile phones, we measured the number of people each hour within a 1km radius of main stations such as Shinjuku, Tokyo, Ikebukuro, Shibuya, Osaka, and Yokohama in Japan. In Figure 1 we show the area within a 1km radius of

Shinjuku Station, and from this we can see various retail facilities located in and around the station.

In Figure 2, we show changes over the course of 24 hours in the number of people within a 1km radius of Shinjuku Station. We sort those present during each time slot into "visitors," "workers," and "residents," based on the GPS of mobile device owners. Whether people are residents or workers in the area is based on mobile device owners' locations during the day and at night. This indicates that most of the people in the area are either "workers" who work in the area or "visitors" on temporary visits to the area. We can also see that the number of workers tends to increase through around 9:00am, and gradually decline from 5:00pm. The number of visitors, meanwhile, increases gradually around lunch time, before peaking at around 6:00pm and decreasing gradually thereafter.

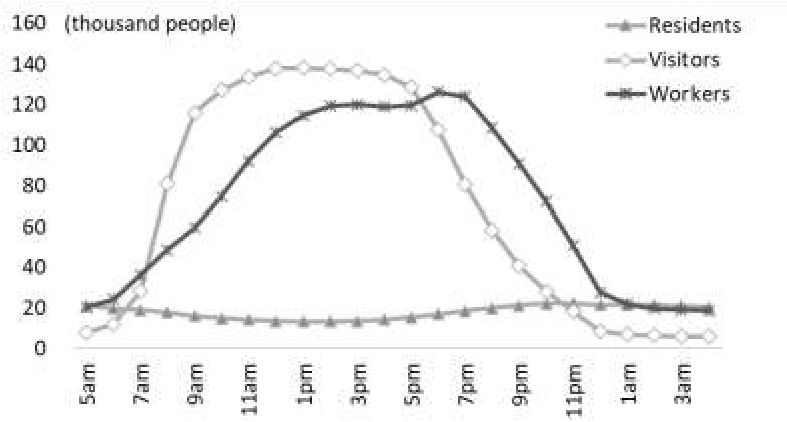

Figure 2: Hourly change in number of people in Shinjuku area

In Figure 3 we show changes in the average number of people per day over the course of one year in each category (residents, workers, and visitors) in the surroundings of Shinjuku Station. While there is some level of seasonal fluctuation, the charts show that the abovementioned hourly trend does not change markedly over the course of the year.

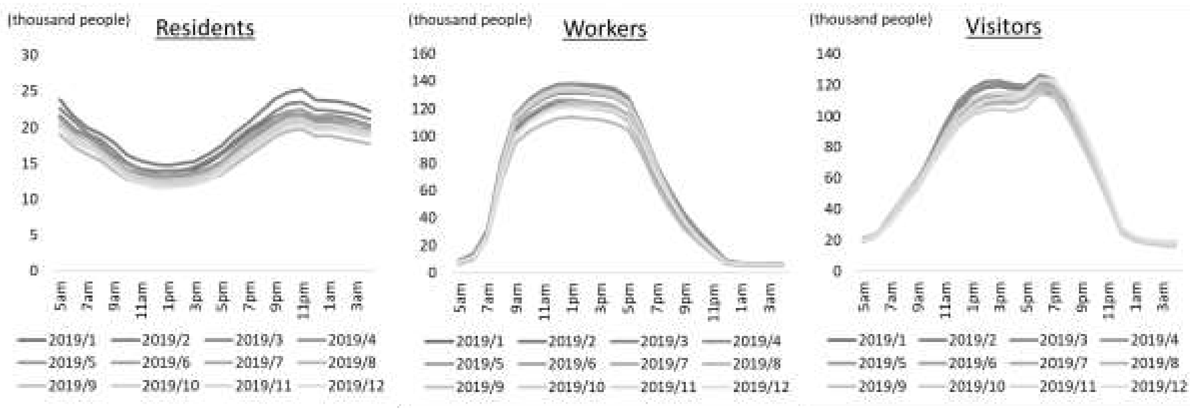

Figure 3: Change in number of people in each category over one year within 1km radius of Shinjuku Station

3 Change in the Number of Visitors in Main Locations

In the previous section, we were able to use mobile phone GPS data to identify changes in the number of people located in the Shinjuku area during the daytime. Since economic activity data are likely to be reflected in some shape or form in the aforementioned data, in this section we focus on visitor data to gain a picture of macroeconomic conditions, and particularly consumer spending. We think it is fair to assume that those visiting these busy shopping areas for other reasons besides the fact that they live or work there are probably there for some kind of consumer spending activity involving either goods or services. In Figure 4 we plot changes in the number of visitors within a 1km radius of the main stations of Shinjuku, Ikebukuro, Tokyo, Shibuya, Osaka-Umeda, and Yokohama. We also measured the number of visitors within a 1km radius of the key tourist sites of Kaminarimon in Asakusa, Tokyo, and Shijo-Karasuma in Kyoto. In this research, we use the visitors' data for weekends/holidays in order to figure out the economic condition.

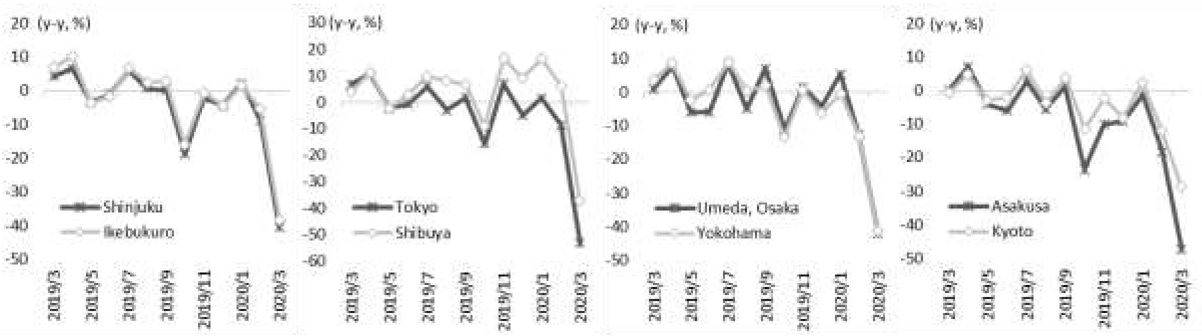

Figure 4: Change in number of visitors at major locations for weekends/holidays

Looking at visitor number data in Figure 4 we can see a broadly similar trend at key locations with a large number of retail facilities in the metropolitan Tokyo area, specifically Shinjuku and Ikebukuro. We can also see a similar pattern at Asakusa (also metropolitan Tokyo) where weather conditions are likely to be the same. Moreover, we can see that the sharp decline in visitor numbers in October 2019, when the consumption tax rate was raised, was not confined to those locations, but occurred across a wide range of areas. That said, we think the decline in the number of visitors may have been attributable to the severe typhoon that hit Japan during the same month. Moreover, in February and March 2020, when people became more aware of COVID-19, there was a notable decline in the number of visitors in the most of regions.

In addition, in Figure 5 below we show the y-y (year-on-year) change in the number of visitors to the Shinjuku area in the second weeks of March in 2019 and 2020, respectively, by age group, in order to ascertain the reasons why people started to refrain from going out in mid-February. As Figure 5 shows, there was a marked y-y decrease in the number of visitors aged 60 and above in both weeks, but declines in visitor numbers in the younger age groups were relatively small. We will leave discussion of the medical details of COVID-19 to the experts, but once they have been infected, the risk that the virus will cause them to become seriously ill is thought to be high for the elder people. We would say that they are therefore likely to be more concerned about the risk of infection than people in other age groups, and appear to have been refraining from going out.

In fact, the studies about patients in the medical field show that risk-averse people are more likely to take active medical and health behaviors [21][22][23][24]. One of the typical actions to avoid the infection risk of Covid-19 is refraining from going out. So, this is consistent with that the tendency of elderly people to refrain from going out. Furthermore, [25] summarizes the studies on the behavioral characteristics of people related to COVID-19.

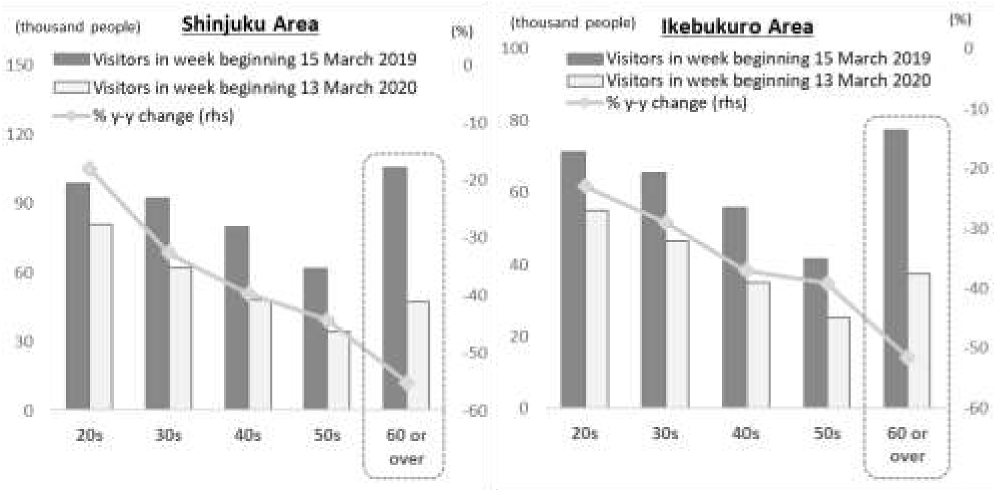

Figure 5: Change in number of visitors to key areas on weekends/holidays, by age group

4 Relationship Between Macroeconomic Indices and Number of Visitors

We now look at how much the above changes in visitor numbers are reflected in actual macroeconomic conditions. TABLE I, II, III show various consumer spending-related government statistics and the correlation coefficient for visitor numbers at various locations (Table I, II, III show correlation coefficients for series period from March through December 2019. Series for Indices of Tertiary Industry Activity (Ministry of Economy, Trade and Industry) and Current Survey of Commerce (Ministry of Economy, Trade and Industry) uses y-y data, Economy Watchers Survey (Cabinet Office) uses current conditions DI data. Series for each location are y-y figures for average number of people per day for each month for weekends/holidays). For example, a strong correlation is evident between the number of visitors to Shinjuku and the amusement/hobbies index in the Indices of Tertiary Industry Activity, and between the number of visitors to Asakusa and the retail-related index of Economic Watcher Survey. As visitors to these locations may well spend on amusement and other services and on retail goods, we think these correlations make sense. Furthermore, as people tend to do more things in such locations when they are upbeat on the economy, it could be considered natural that a correlation can be seen between visitor numbers and spending-related macroeconomic statistics.

Table 1: Correlation between the number of visitors and tertiary industry activity index

		Tertiary Industry Activity Index		
		Amusement/ hobbies	*Food and beverages-related industry*	*Tourism industry*
Major station	*Shinjuku*	0.79	0.71	0.65
	Ikebukuro	0.70	0.70	0.67
	Tokyo	0.65	0.62	0.63
	Shibuya	0.30	0.28	0.37
	Umeda, Osaka	0.42	0.37	0.73
	Yokohama	0.75	0.62	0.66
Tourism destinations	*Asakusa*	0.73	0.72	0.82
	Kyoto	0.67	0.56	0.80

Table 2: Correlation between the number of visitors and current survey of commerce

		Current Surveyof Commerce			
		Retail total	*Retail: food & beverages*	*Retail: fabrics, apparel & accessories*	*Retail: medicine & toiletry stores*
Major station	*Shinjuku*	0.52	0.68	0.31	0.28
	Ikebukuro	0.53	0.65	0.28	0.32
	Tokyo	0.39	0.63	0.23	0.18
	Shibuya	0.23	0.29	0.02	0.22
	Umeda, Osaka	0.46	0.33	-0.07	0.51
	Yokohama	0.46	0.59	0.27	0.28
Tourism destinations	*Asakusa*	0.62	0.70	0.30	0.45
	Kyoto	0.57	0.53	0.22	0.50

Table 3: Correlation between the number of visitors and economic watcher survey

		Economy Watchers Survey		
		Retail-related	*Food & beverage-related*	*Service-related*
Major station	*Shinjuku*	0.72	0.72	0.64
	Ikebukuro	0.72	0.68	0.68
	Tokyo	0.57	0.72	0.64
	Shibuya	0.23	0.52	0.20
	Umeda, Osaka	0.52	0.43	0.40
	Yokohama	0.66	0.57	0.55
Tourism destinations	*Asakusa*	0.83	0.68	0.72
	Kyoto	0.70	0.42	0.48

Based on the relationship between people's behavior and macroeconomic variables, the following analysis focuses on people's consumption behavior while COVID-19 continues to spread. The location data on people's mobile phones can be useful for gaining an insight into their economic activity. To date we have used the location data (GPS data) on mobile phones to measure changes in the number of people in key areas, and have used the findings suggested by these changes to express macroeconomic information in numerical terms. For example, by looking at the number of people visiting major shopping areas such as Shinjuku (the area within a 1km radius of Shinjuku Station), we can gain valuable insights into overall consumer spending in

Japan. Figure 6 shows the actual number of people in the Shinjuku area on weekends and holidays.

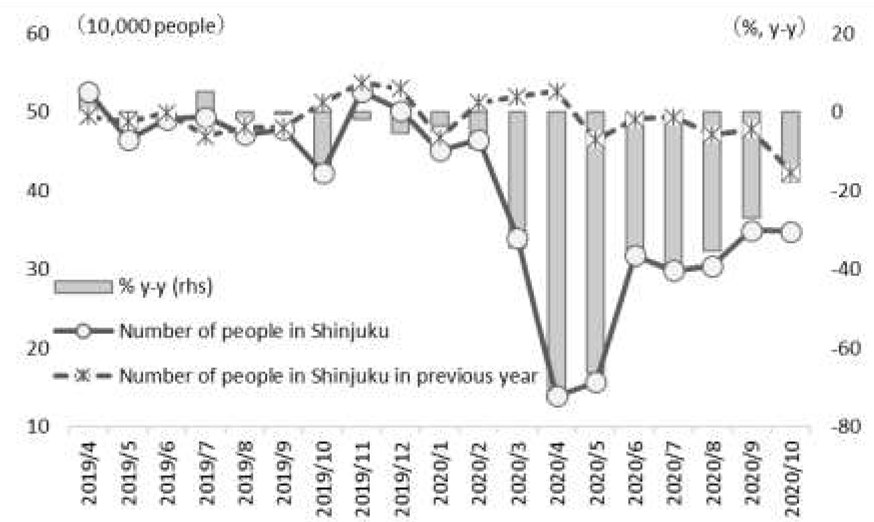

Figure 6: Number of people in the Shinjuku area on weekends and holidays

Below, we conduct a principal component analysis (PCA) to examine the y-y change in the number of people on weekends and public holidays within a 1km radius of major transport hubs in Japan (Tokyo Station, Shinjuku Station, Ikebukuro Station, Shibuya Station, Yokohama Station, Nagoya Station, Osaka Umeda Station, Osaka Namba Station, Kyoto Station, Kobe Sannomiya Station, Kanazawa Station, Sapporo Station, Morioka Station, Sendai Station, and Hakata Station) and use this approach to identify factors that describe people's activity in Japan as a whole.

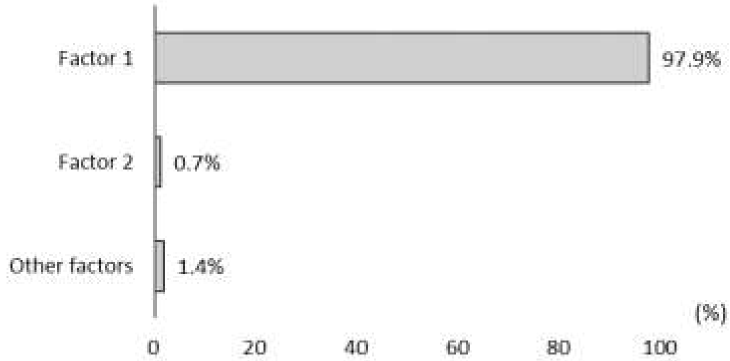

Figure 7: Contributions by top factors based on principal component analysis of people's activity in major locations around Japan

Figure 7 shows the contribution made by each factor in our PCA analysis and confirms that most of the changes can be explained by Factor 1. Below, therefore, we treat PCA Factor 1 as a time series that indicates changes in the number of people out and about in urban areas across the whole of Japan. Figure 8, on the other hand, compares PCA Factor 1 with various consumption indicators.

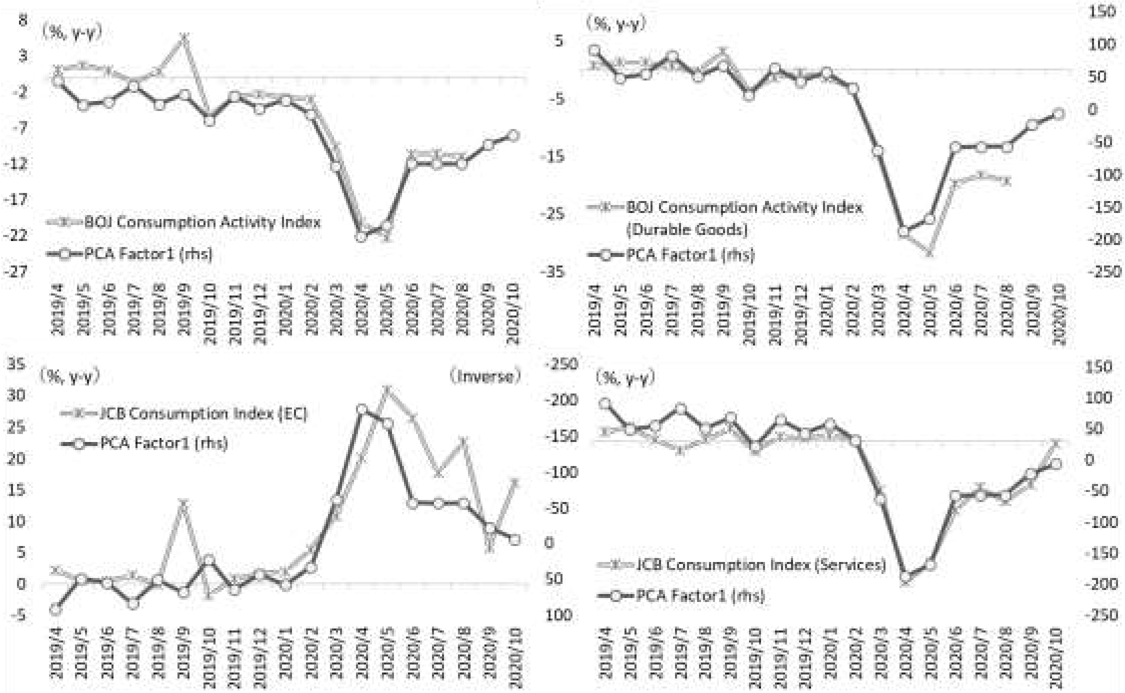

Figure 8: Key macroeconomic consumption data and PCA factor reflecting the number of people out and about

A comparison of PCA Factor 1 with the BOJ's monthly Real Consumption Activity Index (Bank of Japan), shown in the chart in the top left of Figure 8, reveals that the two essentially move in line with each other. Furthermore, of the various consumption indicators shown in Figure 8, those related to the consumption of services show a strong correlation with PCA Factor 1 (Figure 8 top right, bottom right which is the comparison with the data of consumer spending as revealed in credit card payment data from JCB (“JCB Consumption Now” by Nowcast). The correlation between the two is hardly surprising bearing in mind that people often go out to consume services. At the same time, it is also interesting to note that there is a clear inverse correlation between online spending (based on the credit card payment data from JCB) and PCA Factor 1 (Figure 8, bottom left). We think this negative correlation indicates that a change in people's behavior while COVID-19 continues to spread, in the form of staying at home more, led to an increase in online shopping.

5 Conclusion

In order to understand what is happening in the underlying economy, it is useful to gain a picture of what people are doing. For example, when people go out on the weekend, they may do so in order to engage in some kind of economic activity. In this research, we measured the level of economic activity by gaining a macro picture of people's movements. Specifically, we used the location data (GPS data) of mobile phones owned by the customers of major Japanese mobile carrier au to measure changes in the movements of people in key urban areas, and to show the relationship between these changes and macroeconomic variables. Our results found a notable correlation between the number of visitors to Shinjuku area in Tokyo on weekends/holidays and GDP consumer spending and spending-related government statistics such as the Indices of Tertiary Industry Activity and the Current Survey of Commerce. In addition, in Japan, the spread of

COVID-19 has had a marked impact on people's economic activity in 2020. In order to confirm the details of this change, we analyzed the weekly change in the number of visitors to some commercial area in Tokyo. As a result, we confirm that there has been a dramatic change in people's behavior since the middle of February, when people became more aware of COVID-19 in Japan. Especially, we confirmed that a sharp decline in the number of visitors aged 60 or above. Meanwhile, declines in visitor numbers in the younger age groups were relatively small in March. Once they have been infected, the risk that the virus will cause them to become seriously ill is thought to be high for the elderly. We would say that they are therefore likely to be more concerned about the risk of infection than people in other age groups, and appear to have been refraining from going out. Furthermore, according to the result of the comparison between the people's movements and the macro consumption indicators, we found that the people's movements has a strong correlation with the consumption data of services. At the same time, we found that there is a clear inverse correlation between online spending and the people's movements. This negative correlation indicates that a change in people's behavior while COVID-19 continues to spread, in the form of staying at home more, led to an increase in online shopping.

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