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Price Index Numbers Under Large-Scale Demand Shocks - The Japanese Experience of the COVID-19 Pandemic*

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Abstract

This study examines the effects of the coronavirus disease 2019 (COVID-19) pandemic on consumer price indices using Japanese face mask scanner data. We show that the COVID-19 pandemic causes a shift in consumers' preferences to a large extent, and the Paasche index becomes greater than the Laspeyres index. When large-scale changes in preferences occur, the standard superlative index, such as the Fisher or Tornqvist indices, are hard to be regarded as the cost of living index (COLI) defined based on consumer theory. Using a recently developed index number formula that is exact for the constant elasticity of the substitution utility function with variable preferences, we quantify the degree of the demand shock caused by the COVID-19 pandemic. We also show that shifts in preferences are so large that by incorporating the changes in preferences, the COLI becomes very different from the standard superlative indices. While the prices of face masks became lower in the Fisher index in May 2020 by 0.76% per week, the COLI increased by 1.92% per week. The magnitude of the bias caused by the demand shock is so substantial that traditional index numbers might carry the wrong information on the cost of living among consumers.

Keywords COVID-19, Pandemic, Coronavirus, Price Index, Demand shocks

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1. Introduction

The global coronavirus disease 2019 (COVID-19) pandemic caused massive stockpiling behaviors among consumers and long queues at the doors of many retailers all over the world. Japan is no exception. The first case of COVID-19 in Japan was reported in mid-January 2020. Immediately after the news was reported, the demand for face masks and sanitizers surged. On March 23, 2020, the governor of Tokyo warned that the city might require a lockdown, which made many people rush to supermarkets and grocery stores to purchase various kinds of foods and other necessary items.

Because of the COVID-19 threat, people changed their consumption behaviors to a large extent. Figure 1 shows the movements of the weekly rates of change of the chained Laspeyres and Paasche indices of face masks in Japan based on scanner data[1]. In general, due to bargain sales, high-frequency scanner data often exhibit large discrepancies between Laspeyres and Paasche indices, which we can observe in the figure until 2020. In the middle of January 2020, both indices increased to a great extent; then, the Paasche index overtook the Laspeyres index. According to the Bortkiewicz decomposition of the Laspeyres-Paasche (L-S) gap, the negative L-S gap implies that the correlation between quantities and prices is positive. Although theoretically, a positive correlation between quantities and prices is not impossible, it is quite unlikely. A natural interpretation is that during the period, large-scale demand shocks occurred, which shifted the prices and quantities along an upward-sloping supply curve.

The standard theory of the consumer price index relies heavily on consumer theory. Since the pioneering works by Edgeworth in the 19th century, an economic approach of the index number has

[1] Section 4 examines detailed information on the dataset we use in this study.

been developed by Konus (1924), Frisch (1936), Samuelson and Swamy (1974), Sato (1976), and Vartia (1976) that led to the seminal works by Diewert (1976)—the superlative index. Although these impressive results have formed the foundation of the modern index number theory, there has been little effort devoted to investigating the relationship between changes in preferences and the cost of living[2]. When large-scale demands shocks occur, the superlative index, such as the Fisher index and the quasi-superlative index such as the Sato-Vartia index, is no longer the cost of living indices (COLI) based on constant preferences. That is, the interpretation of these index numbers becomes difficult when demand shocks occur. The case during the COVID-19 is particularly serious, considering the scale of demand shocks that are so big that the L-S gap based on scanner data becomes negative.

Recently, in a path-breaking paper, Redding and Weinstein (2020) propose the constant elasticity of substitution (CES) unified price index (CUPI) with heterogeneous preferences. The novelty of the index number is that the index is always the COLI for all the observed quantities and prices. This is in sharp contrast with the superlative index that is a COLI only when the quantities are on the time-invariable demand functions. In other words, the superlative indices are COLIs only for a limited set of quantities and prices, which causes discrepancies between data and theory in general. More specifically, if quantities are on the demand function, the COLI must be transitive, as Samuelson and Swamy (1974) state. However, as de Haan and van der Grient (2011) stress, the superlative indices often exhibit a strong chain drift, which indicates that there is a discrepancy between data and

[2] One notable exception is Fisher and Shell (1972) that proposes calculating the difference between two cost of living indices (COLIs), one using the old preferences, and one using the new preference. Although this carries information on the effects of having different preferences on the COLI, it does not provide us with information on how the cost of living changes when preferences change. Phlips (1974) criticizes Fisher and Shell (1972) and proposes a cardinal COLI that compares the minimum expenditures between two time periods assuming two different utility levels are comparable, that is, the utility function is cardinal. Balk (1989) proposes a COLI based on ordinal utility functions. He introduces the reference vector. The minimum expenditure is arrived at which the utility level at the reference vector are assured.

theory. The CUPI by Redding and Weinstein (2020) is not only exact for a class of utility function, but the index is also known to be transitive[3], which provides us with an index number that is always consistent with consumer theory[4]. Therefore, the CUPI provides us with an appropriate tool to evaluate the impacts of COVID-19 on the cost of living.

In this study, using Japanese weekly scanner data, we quantified the degree of demand shocks caused by the COVI-19, which turned out to be substantial. We also found that during the COVID-19 pandemic, the traditional superlative index, as well as the Sato-Vartia index become negative while the CUPI is positive and increasing, which indicates a large "bias" in the superlative index. More specifically, while the prices of face masks become lower in the Jevons and Fisher indices in May 2020 by 0.06% and 0.76% per week, respectively, the COLI increased by 1.92% per week. The magnitude of the bias caused by the demand shock is so substantial that traditional index numbers might carry the wrong information on the cost of living among consumers.

The paper is organized as follows. Section 2 presents a brief history of the COVID-19 pandemic in Japan. Section 3 introduces the index number formula by Redding and Weinstein (2020) and discusses the measures of demand shocks. Section 4 explains our dataset. Section 5 reports our empirical results. Section 6 concludes.

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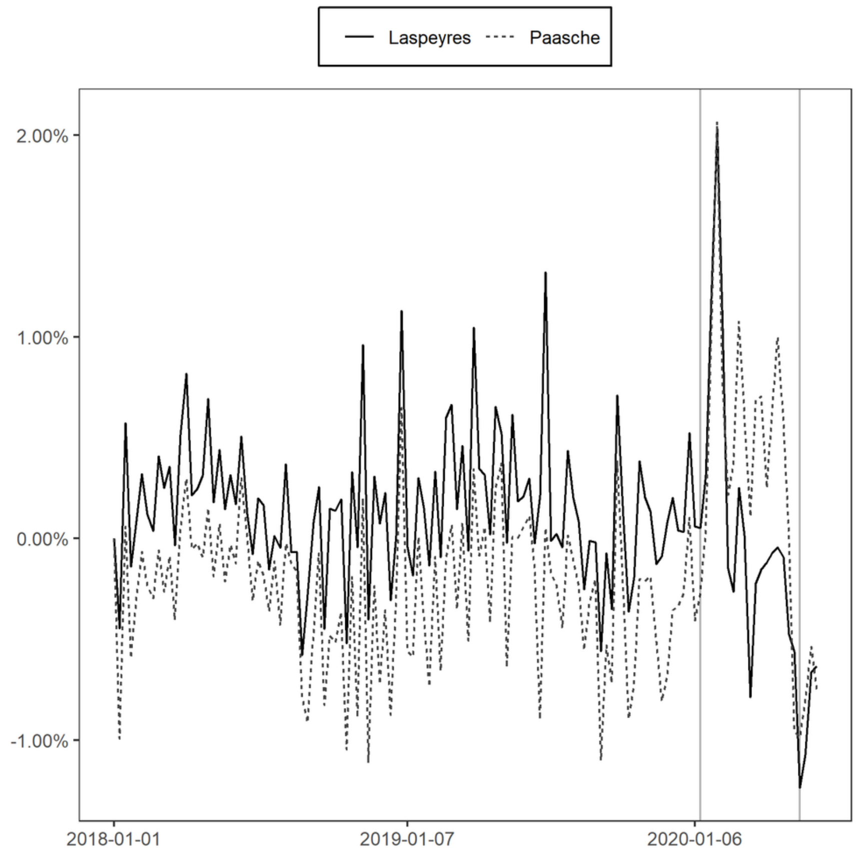
[3][3] Abe and Rao (2020) show that the CUPI satisfies transitivity, commensurability, monotonicity, and linear homogeneity. However, the index does not pass the identity test.

[4] To construct the CUPI, all the quantities must be strictly positive.

Figure 1: The Laspeyres and Paasche Indices of Face Masks

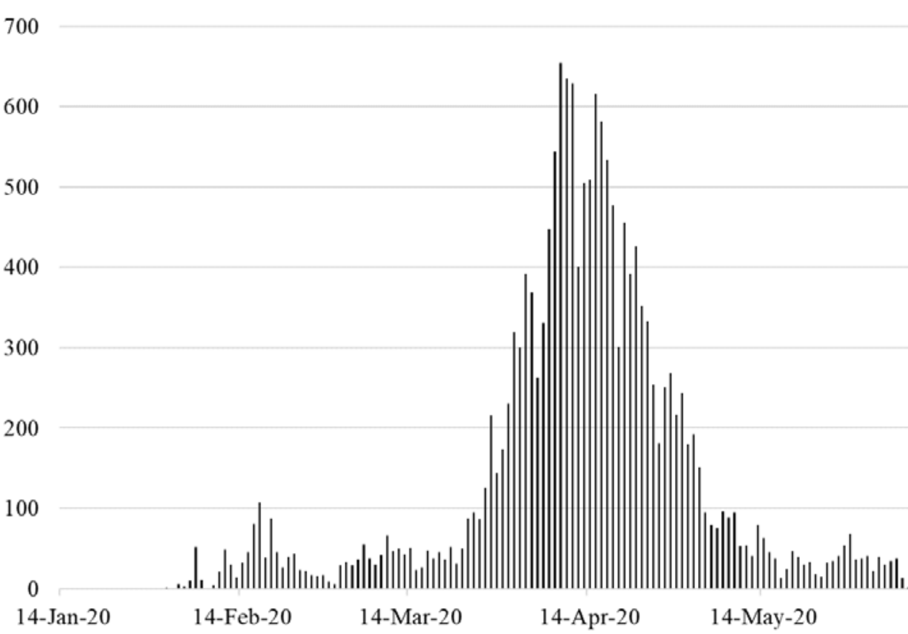


Notes: Based on Japanese Scanner data. See Section 5 for the detail of the dataset.

2. COVID-19 in Japan and Face Masks

The first case of COVID-19 outside the Republic of China was in Thailand on January 13, 2020. Three days later, on January 16, 2020, Japan became the second country to report the infection outside China. Figure 2 and Table 1 show the number of COVID-19 cases in Japan by reported date and the Japanese government's response to the COVID-19 pandemic, respectively. On February 2, it was confirmed that a passenger on the Diamond Princess cruise ship was infected, and on the following day, the ship was put under quarantine. While the case of the Diamond Princess attracted much attention all over the world, the number of cases in Japan was quite limited in January. As Figure 2 indicates, the number of infections began to increase in February. On February 13, the Japanese government declared the first emergency response plan. Under the emergency response plan, manufacturers are asked to increase the production of masks that are already in short supply, and prefectures are asked to allocate the stockpile of masks to medical institutions that have a shortage of medical masks.

Figure 2: The Number of Infections of COVID-19 in Japan



Source: The National Institute of Infectious Diseases, Japan.

Table 1: Timetable of COVID-19 in Japan

16-Jan-20	The first confirmed case.
2-Feb-20	A passenger of the Diamond Princess cruise was tested positive for COVID-19.
13-Feb-20	The government decided on an emergency response plan.
27-Feb-20	The government requested the closure of all elementary, junior high, and high schools.
10-Mar-20	The government decided on the second phase of the emergency response plan.
23-Mar-20	The Tokyo governor warned that Tokyo might be lockdown, which caused massive stockpiling behavior.
7-Apr-20	The government declared emergency.
16-Apr-20	The scope of the emergency declaration was expanded to all prefectures.
14-May-20	The government partially lifted the state of emergency.
24-May-20	The government lifted the state of emergency.

Two weeks later, all elementary, junior high, and high schools were asked to shut down their campuses. On March 10, the second phase of the emergency response plan was formulated, which included the establishment of a new subsidy system for temporary school closures. As a part of the emergency measure, the government decided to legally prohibit the resale of masks, which were still in short supply. The government also began to purchase 20 million reusable cloth masks in bulk for distribution to nursing care facilities and nursery schools. Furthermore, the government decided to secure 15 million masks for distribution to medical institutions on a priority basis by expanding imports and asking manufacturers to increase production.

Since the infection was confirmed to have continued, the governor of Tokyo mentioned the possibility of a lockdown at a press conference held on March 23. As a result, there was a temporary increase in consumer demand for food and household goods. On April 7, the government declared a state of emergency in seven prefectures, including Tokyo and Osaka, for a month and asked the public to avoid moving out of the prefecture as much as possible. In response to the continuing shortage of masks, the government decided to distribute two reusable cloth masks to each child, student, and faculty member attending school across the country, as well as two masks to every household at each address. The distribution of these cloth masks to all households was completed on June 20. On April

16, the scope of the emergency declaration was expanded to all prefectures, and a proposal for the payment of 100,000 yen per person was posted as economic support for the people. On May 4, it was decided to extend the declaration of a state of emergency until May 31. However, on May 14, the government lifted the declaration of a state of emergency in 39 of the 43 prefectures as the number of infected people decreased. The declaration was lifted for three more prefectures on May 21, and on May 25, the full emergency declaration was lifted ahead of schedule.

The government asked manufacturers to increase the production of masks since February if that year. However, both manufacturers and retailers seemed to expect the surge in demand for face masks in January. Unicharm, a major manufacturer of hygiene products, had already decided to provide a 24-hour supply from the next day, after a sharp increase in orders from retailers on January 16. There may have been an increase in the demand for masks for people who were planning to return to China from Japan for the Chinese New Year holiday, and who purchased masks in Japan before returning home. Since the beginning of February 2020, high resale prices of masks have been confirmed on internet sales sites and auction sites. Since then, the demand for masks in Japan has continued to be high in comparison to normal times.

3. The Price and Cost of Living Index with Taste Shocks

The CUPI by Redding and Weinstein (2020) consists of the two price indices. The first is the CES common variety (CCV) price index, and the second is the Redding-Weinstein (RW) index that includes the effects of changing product variety. The CCV between time s and t is defined as

$$\ln CCV\left(p_s, q_s, p_t, q_t\right) = \sum_{i=1}^{N} \omega_{ist}^{*}\left(\ln p_{it} - \ln p_{is}\right) + \sum_{i=1}^{N} \omega_{ist}^{*}\left(\ln \varphi_{is} - \ln \varphi_{it}\right), \qquad (1)$$

$$\omega_{ist}^{*} = \frac{w_{it} - w_{is}}{\ln\left(w_{it}\right) - \ln\left(w_{is}\right)} / \sum_{i=1}^{N} \frac{w_{it} - w_{is}}{\ln\left(w_{it}\right) - \ln\left(w_{is}\right)}, \tag{2}$$

$$w_{it} = p_{it} q_{it} / \sum_{i=1}^{N} p_{it} q_{it}, \tag{3}$$

where φ_{it} and q_{it} are the taste parameter and the quantity of a commodity i, at time t, respectively. Note that we denote the vector of prices, quantities, and taste parameters at time t as

$$p_t = \left(p_{1t}, p_{2t}, ..., p_{Nt}\right),\ q_t = \left(q_{1t}, q_{2t}, ..., q_{Nt}\right),\ \varphi_t = \left(\varphi_{1t}, \varphi_{2t}, ..., \varphi_{Nt}\right).$$

The taste parameter φ_{it}, is also a function of prices and quantities as follows,[5]

$$\varphi_{it} = \left(\frac{p_{it}}{p_{1t}}\right)\left(\frac{w_{it}}{w_{1t}}\right)^{\frac{1}{\sigma-1}} \left[\prod_{k=2}^{N} \left\{\left(\frac{p_{kt}}{p_{1t}}\right)\left(\frac{w_{kt}}{w_{1t}}\right)^{\frac{1}{\sigma-1}}\right\}^{(-1/N)}\right] \varphi. \tag{4}$$

The first term in the right-hand side of equation (1) is the Sato-Vartia (SV) index. The second term is called the taste-shock bias that makes the difference between the CCV and the SV index. Redding and Weinstein (2020) show that equation (1) is the COLI for the following utility function and the normalization condition,

$$U_t\left(q_t; \varphi_t, \sigma\right) = \left(\sum_{i=1}^{N} \left(\varphi_{it} q_{it}\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{5}$$

$$\prod_{i=1}^{N} \varphi_{it} = \varphi, \tag{6}$$

where $\sigma > 1$ is the elasticity of substitution, while $N > 1$ is the number of commodities. Because

5 Please see the Appendix A for the derivation of equation (4).

the above utility function is linear homogeneous, the minimum expenditure function can be written as the product of the unit expenditure function, $C\left(p_t;\varphi_t\right)$ and the utility level,

$$E\left(p_t,U_t;\varphi_t\right)=C\left(p_t;\varphi_t\right)\times U_t,$$

where the unit expenditure function takes the following functional form,

$$C\left(p_t;\varphi_t\right)=\left(\sum_{i=1}^{N}\left(\frac{p_{it}}{\varphi_{it}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}.$$

The notable feature of the utility function in equation (5), is that the taste parameter, φ_{it}, can vary over time. Thus, when defining the cost of living index, Redding and Weinstein (2020) adopt the following COLI based on the assumption that utility is cardinal

$$COLI\left(s,t\right)=\frac{E\left(p_t,U_t=U;\varphi_t\right)}{E\left(p_s,U_s=U;\varphi_s\right)},$$

$$=\frac{C\left(p_t;\varphi_t\right)\times U}{C\left(p_s;\varphi_s\right)\times U},$$

$$=\frac{C\left(p_t;\varphi_t\right)}{C\left(p_s;\varphi_s\right)}.$$

It is worth noting that from the observed quantities and prices, it is impossible to identify all the taste parameters, φ_t. For example, suppose we multiply all the taste parameters by a constant, $\kappa>0$, then, the preferences will generate identical demand functions but different values for the COLI. Therefore, we need an additional exogenous condition to identify the taste parameters. Redding and Weinstein (2020) consider various kinds of conditions and adopt equation (6) as the first choice. This identification problem might seem very serious because the choice of the normalization condition affects the index number. Recently, Abe and Rao (2020) show that the normalization condition in the form of the geometric mean is necessary for the CCV to pass the commensurability test, which is one of the fundamental axioms for price index number formulae. That is if we adopt the arithmetic mean, such as $\left(1/N\right)\sum_{i=1}^{N}\varphi_{it}=\varphi$, the CCV will become sensitive to the choice of the measurement units of commodities such as the pound or the kilogram[6]. Therefore, in this study, we also use equation $\left(6\right)$ as the normalization condition.

A demand shock for commodity i occurs at time t when the taste parameter changes at time t, that is, when we have the following,

$$\varphi_{it}\neq\varphi_{it-1}.$$

If taste parameters change over time, then the preference is also changing over time. In such a case, it is possible to show that the SV index is no longer the COLI for the CES function. In other words, if the SV index is the COLI, for all the commodities and time, we must have

$$\varphi_{it}=\varphi_{it-1}.$$

Note that using equation $\left(4\right)$, we can compute the taste parameter, φ_{it}, from the expenditure shares and prices at time t. It is quite rare that the above equality holds. A natural measure of the degree of the demand shock at t is the root-mean-square deviation such as[7],

$$RMSD_t=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\ln\varphi_{it}-\ln\varphi_{it-1}\right)^2}. \tag{7}$$

If the root mean squares deviation (RMSD) increases, then the departure between the SV and the COLI is expected to be greater. The actual effects of the demand shock on the price index can be captured by the taste-shock bias in $\left(1\right)$, $\sum_{i=1}^{N}\omega_{ist}^{*}\left(\ln\varphi_{is}-\ln\varphi_{it}\right)$.

[6] Abe and Rao (2020) show that the CCV passes the transitivity test as well as the monotonicity test but fails to pass the identity test.
[7] Note that due to the normalization condition, the simple geometric average of the taste parameters is always constant.

As Redding and Weinstein (2020) found, it is not difficult to generalize the CCV so that the utility functions can take the form of the translog function with variable taste parameters. Note that the Tornqvist index is equal to the COLI only when the structural parameters in the utility function are constant over time. As Diewert (1976) points out, the translog function is flexible, which enables us to make the Tornqvist index be a good approximation of the COLI for any twice continuously differentiable utility functions. However, the translog, or quadratic mean of order *r*, is not flexible enough to make the Tornqvist and Fisher indices at different time periods be the COLI for the identical utility function. The CCV by Redding and Weinstein (2020) is the COLI at any time, which is in sharp contrast with the standard superlative index as well as the SV index.

4. Data

In this study, we use the scanner data of face masks provided by Intage Holdings Inc. The dataset contains the barcode level weekly sales and quantity information from nationwide retail stores in Japan. We chose data for face masks between the week starting January 1, 2018, and the week starting June 8, 2020. The scanner data provided by Intage is the largest point of sales data in Japan collected from more than 3000 various retail stores such as general merchandise stores, supermarkets, convenience stores, and drug stores all over Japan. Moreover, the retailers are chosen so that we can regard the data as the national representative sample. In Table 2, we report descriptive statistics for each weekly aggregated variable. As shown in the first row, the maximum value of the total sales is very large compared to the 95th percentile point. This distortion of the distribution of sales is due to the week when the demand for masks increased sharply in January 2020, as shown in Figure 3. It shows the movements of the total sales of face masks. From the second row to the fifth row, we report the mean and standard deviation of the log change in prices and expenditure shares in the common product calculated per week. The table shows that changes in expenditure shares are more volatile than changes in prices.

Table 2: The Descriptive Statistics of Face Masks in Japan

	mean	Std. dev	min	P5	P25	P50	P75	P95	max
Total Sales (million yen)	101	131	16.4	19.3	31.7	86.5	130	200	1330
Mean Δ(ln Price) (%)	-0.03	0.26	-0.49	-0.43	-0.19	-0.05	0.12	0.39	1
Std. Dev. Δ(ln Price)	0.07	0.01	0.05	0.06	0.07	0.08	0.08	0.08	0.09
Mean Δ(ln Share) (%)	0.77	6.48	-41.3	-6.09	-1.87	0.44	3.09	10.7	21.6
Std. Dev Δ(ln Share)	0.8	0.16	0.69	0.7	0.72	0.74	0.75	1.18	1.29

Notes: Scanner data of face masks between the week starting January 1, 2018, and the week starting June 8, 2020. Data is provided by Intage, covering about 3000 retail stores all over Japan.

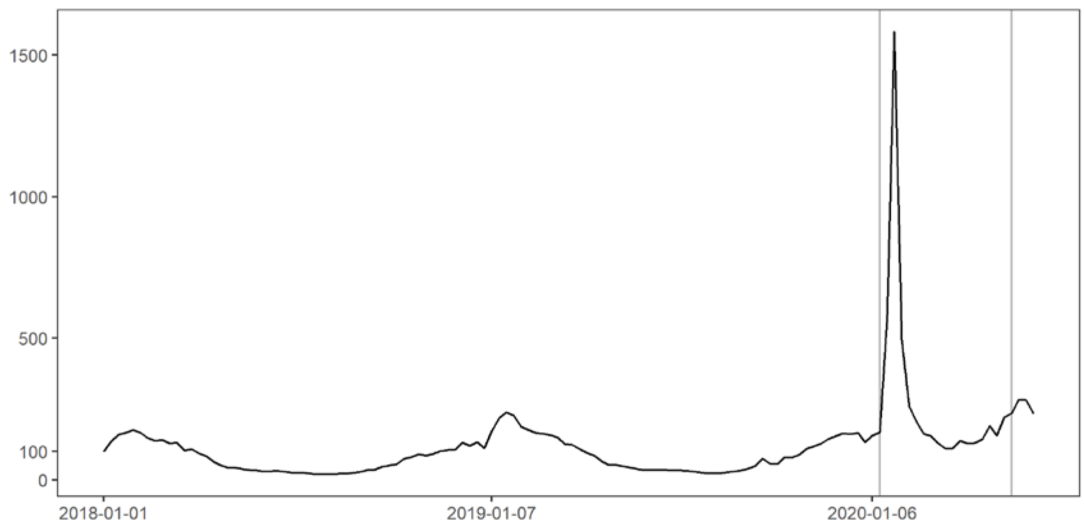
Table 3: Differences in some statistics before and after the start of the COVID-19 outbreak

	2020	2018-2019	P
Sales (million yen)	235	102	0.059
	(285)	(47)	
Mean Δln Price (%)	0.224	0.029	0.015
	(0.286)	(0.225)	
Std. Dev. Δln Price	0.063	0.075	<0.001
	(0.008)	(0.003)	
Mean Δln Share (%)	3.45	1.21	0.485
	(13.495)	(2.927)	
Std. Dev. Δln Share	1.14	0.742	<0.001
	(0.122)	(0.009)	

Notes: The standard deviation of each statistic is in parenthesis. The statistics of 2020 are calculated from a sample under the COVID-19 disasters from the week starting January 13 to May 18, 2020. The data for 2018 and 2019 are selected to correspond to the same week as the 2020 COVID-19 outbreak, counted from the beginning of the year. Specifically, we select the period between the week starting January 8, 2018, and the week starting May 14, 2018, and the period between the week starting January 14, 2019, and the week starting May 20, 2019.

Table 3 shows the changes in each statistic during the COVID-19 period. The second column reports the average of each statistic for the period of the COVID-19 pandemic, which is the second to the twentieth week from the beginning of the year. The third column contains the average of each statistic for weeks 2 through to week 20 in 2018 and 2019. The fourth column reports the p-values of the t-tests of the statistics for 2020 and 2018-2019. Although average sales increased during the COVID-19 period to a great extent, it is not significant on a 5% basis. Besides, changes in the log prices and log shares exhibit statistically significant differences between the COVID-19 period and other periods. As shown in the second row, the average of the log changes in prices slightly increases. The standard deviation of the log change in prices in the third row decreases significantly during the COVID-19 period. On the contrary, the standard deviation of the log change in expenditure share in the fifth row shows a significant increase during the COVID-19 period.

Figure 3: Movements of the Total Sales of Face Masks



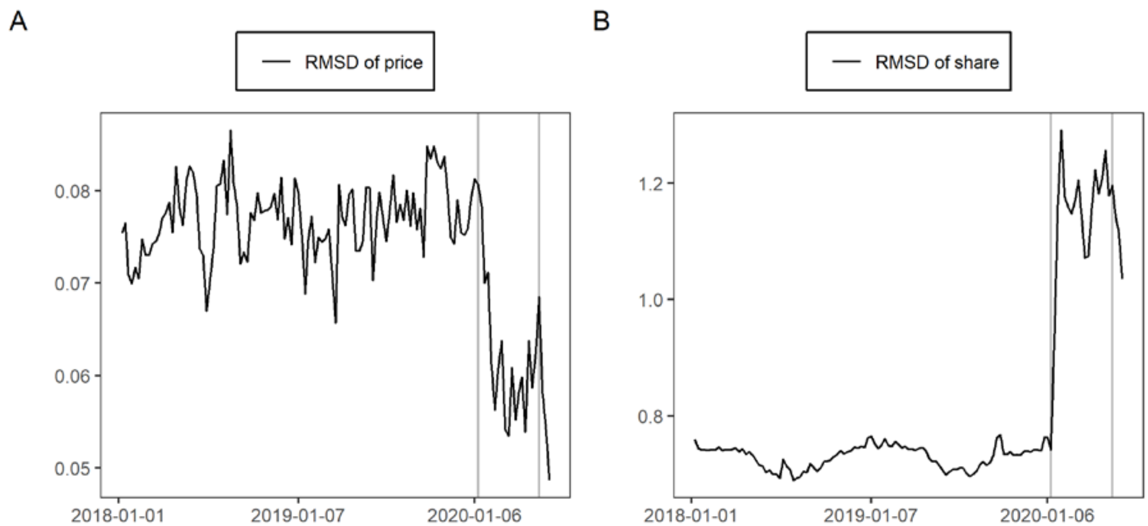
Notes: Source: Scanner data provided by Image. Total sales in the first week of 2018 are normalized as 100.

Figure 3 depicts the changes in the total sales of face masks in our dataset. Note that we identify a commodity by a combination of the commodity code and the retailer. That is, if two commodities with identical commodity codes (Japanese Article Number, JAN) are sold at different stores, they are treated as different commodities[8]. The period of the COVID-19 pandemic is set as

[8] Although JAN code is supposed to be the unique identifier of products, sometimes, manufactures keep the identical JAN codes when they change the contents of the products. To deal with this problem, Intage creates an additional code, sequential code, to identify the difference of the commodities with the identical JAN codes if there are any differences. In this paper, as the commodity identifier, we use the combination of both JAN and sequential codes. The total number of commodities × stores is about 47,000.

the period between the week starting January 13, 2020, and the week starting May 18, 2020. This period is illustrated as the interval between two vertical grey lines in Figure 3. We can observe clear seasonality in Figure 3, probably reflecting the seasons of infectious diseases such as influenza. The impact of COVID-19 is very clear.

Figure 4: Movements of the RMSD of Prices and Shares of Face Masks in Japan



Notes: Source: Scanner data provided by Image.

Figure 4 reports the RMSD of (logged) prices and (logged) expenditure shares. In the first week of the COVID-19 pandemic, prices become less volatile while the fluctuation of market shares surged. If the demand curve is stable, smaller volatility in prices should come with stable market shares. Thus, Figure 4 suggests that the demand curve changes in the first week of the COVID-19 pandemic.

5. Empirical Results

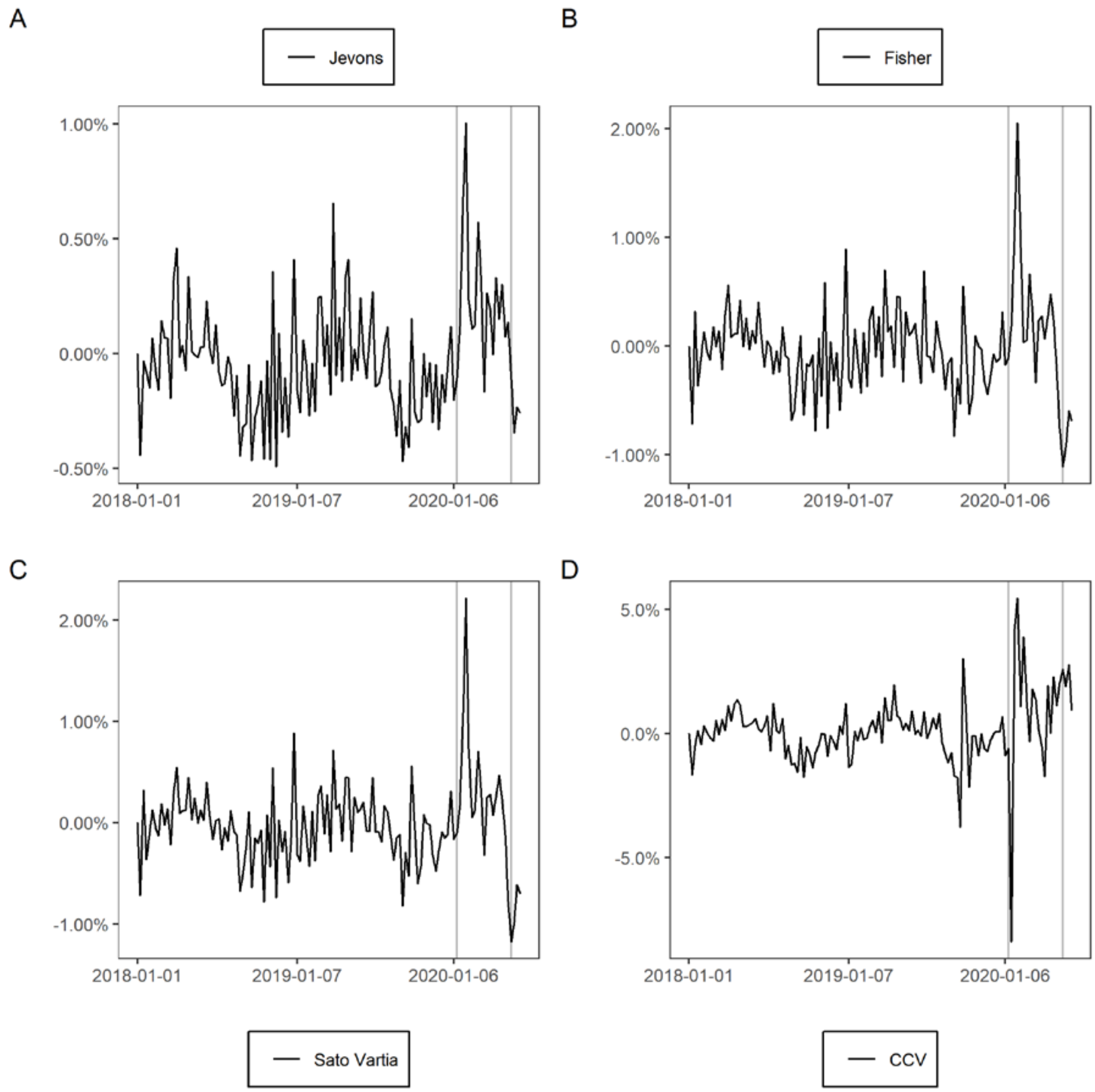
Figure 5 shows the weekly change rates of several chained price indices. Panel A exhibits the movements of the simple geometric average price, the Jevons index, which is known to be free from the chain drift. Panels B and C report the movements of the Fisher and SV indices, respectively. The Fisher and SV indices are also very close to each other. Although not depicted in the figure, the Tornqvist index is also very close to the Fisher index. The Jevons, Fisher, and SV indices exhibit a sharp increase in the first week of the COVID-19 period. However, when we consider the changes in the preferences, the movements of prices become very different. The CCV shows a sharp drop in prices in the first week of the COVID-19 pandemic, which then increased to a large extent[9]. Table 4 summarizes movements of the indices. In May 2019, the CCV is greater than the Sato-Vartia, suggesting that the bias term in (1) is positive. The existence of positive bias is consistent with the results by Redding and Weinstein (2020). In May 2020, the discrepancies between the unweighted geometric means of prices (the Jevons index) and the Fisher index increased. While the Jevons index shows that the average rate of weekly changes in May is -0.06%, Both the Fisher and Sato-Vartia indices are -0.76%. The CCV showed an increase in the prices by 1.92% per week, suggesting that the biases caused by the demand shocks are substantial.

Figure 6 shows the movement of the RMSD of taste parameters (Panel A) and the taste shock

[9] The point estimate of the elasticity of substation is 5.87, which is between the 25th and 50th percentiles reported by Redding and Weinstein (2020). We adopt the methods developed by Feenstra (1994) to estimate the elasticity of substitution using balanced data during 2018-2019. We chose the periods because if we include observations during 2020, the estimates become unstable. The constant elasticity over time is surely a restrictive assumption. However, the estimation methods by Feenstra (1994) and Redding and Weinstein (2020) as well as the CCV critically depend on the assumption that the elasticity of substitution is constant over time. The considerations of variable elasticity will be our future tasks.

defined as $\sum_{i=1}^{N} \omega_{ist}^{*} \left(\ln \varphi_{is} - \ln \varphi_{it} \right)$ (Panel B). First of all, from Panel A, we can observe that the RMSD of the taste parameters are always positive even before the COVID-19 period, which indicates that the Sato-Vartia is not the COLI for the CES utility function with constant taste parameters. The discrepancies increased rapidly and remained at relatively high levels during the COVID-19 period. The effects of the changes in the taste on the COLI is depicted in Panel B in Figure 6. In the first week, the taste shock decreased the COLI to a large extent. The intuition behind the drop is as follows. In the market for face masks, some products have large market shares, while others have small shares. Suppose the COVID-19 pandemic led people to purchase fewer masks more than they did before the COVID-19. Then, the expenditure shares of face masks will be more equalized. As Redding and Weinstein (2020) argue, consumers value dispersion in prices across commodities if these commodities are substitutes (σ>1). Thus, such increases in diversity will decrease the cost of living. However, this is only a one time shock. Soon after achieving a relatively high degree of diversity, its negative shock diminished. After the second week of the start of the COVID-19 period, the taste shock fluctuates, reflecting the diversity of the expenditure shares of the commodities. If the market shares of commodities began to concentrate, the taste shock became positive, which actually happened after the second week of the COVID-19 outbreak.

Figure 5: Weekly Change Rates of Several Price Indices of Face Masks



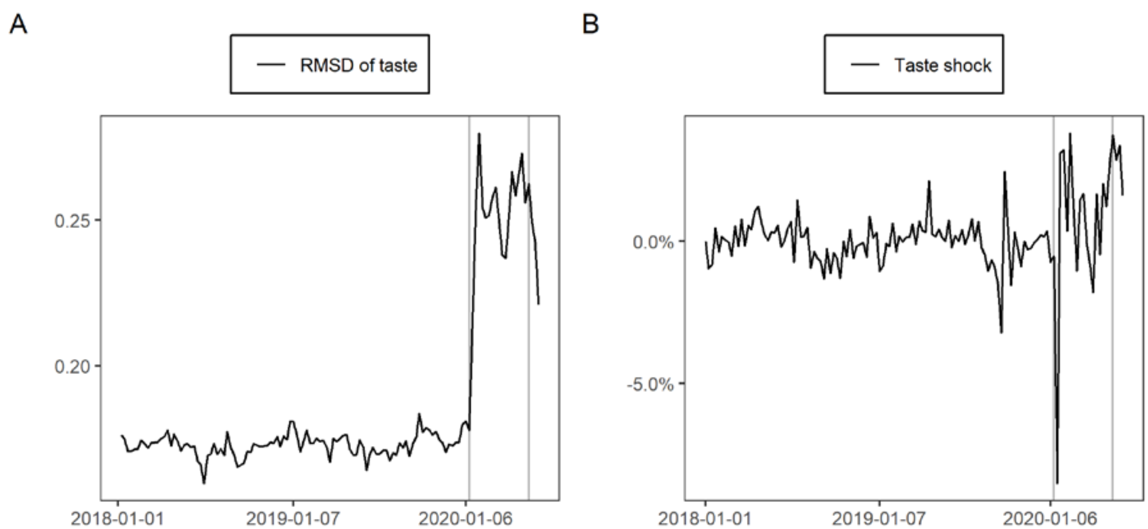
Notes: The weekly change rates of chained indices. CCV stands for CES common variety price index defined in equation (1).

Table 4: Comparisons of Price Indices in May, 2020

	Jevons	Fisher	Sato Vartia	CCV
2020/5/4	0.07	-0.23	-0.12	1.13
2020/5/11	0.14	-0.76	-0.78	2.05
2020/5/18	-0.11	-1.11	-1.17	2.59
2020/5/25	-0.34	-0.94	-0.98	1.90
Average. May, 2020	-0.06	-0.76	-0.76	1.92
May, 2018	0.00	0.09	0.10	0.33
May, 2019	0.06	0.13	0.13	0.33

Notes: The weekly rates of change (%) of the chained indices. More comprehensive numbers are reported in the Appendix Table

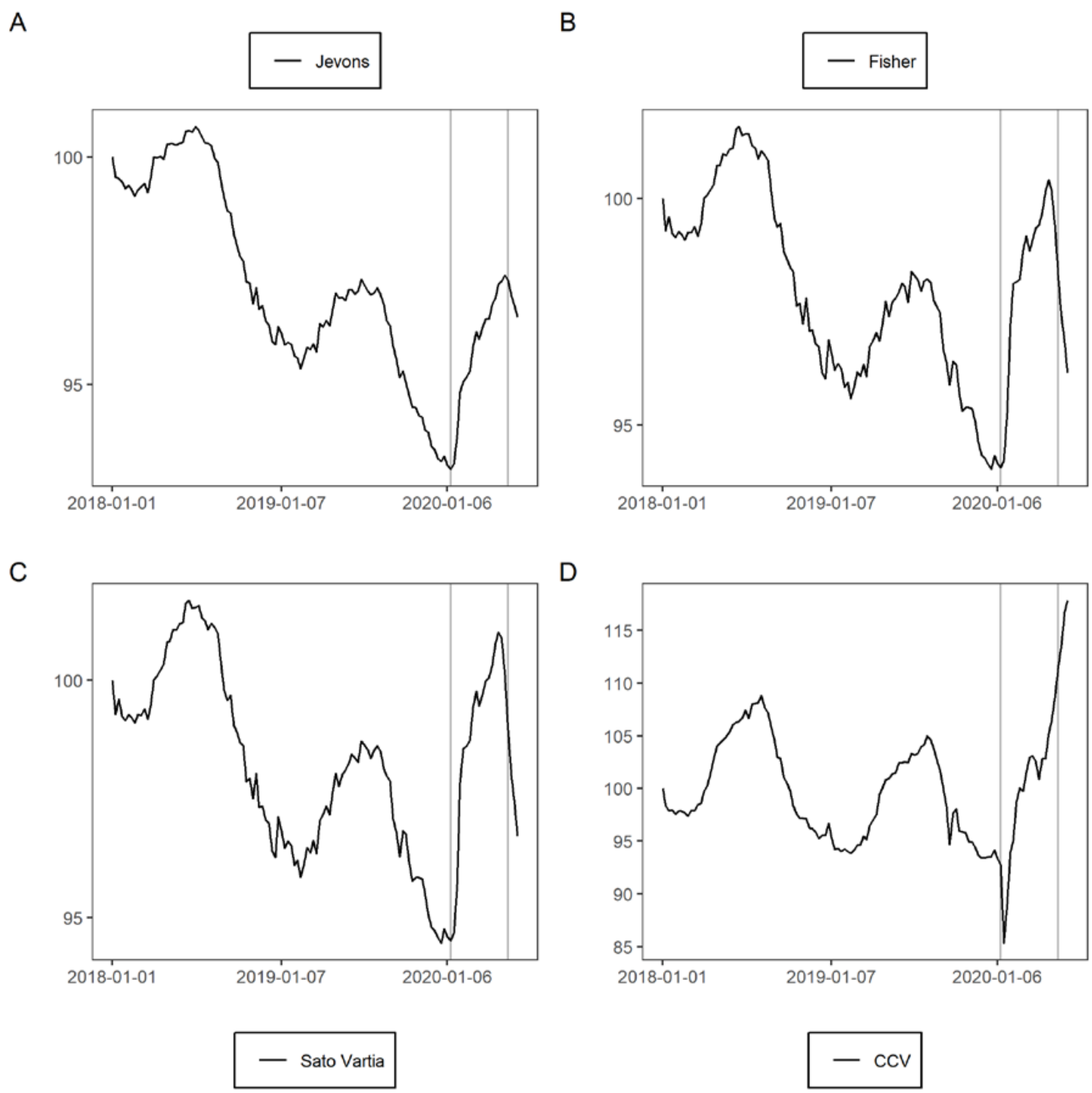
Figure 6: The RMSD of Taste Parameters and the Taste Shock



Notes: RMSD of taste is defined in (7), while the taste shock is defined as the second term of the R.H.S. of (1).

Figure 7 shows the level of several price indices. A notable feature is the difference between the CCV and other price indices after the middle of the COVID-19 period. The Jevons, Fisher, and SV indices became smaller after May, while the CCV kept increasing. In early June 2020, the Jevons, Fisher, and SV indices are around 97, while the CCV is over 115. In other words, the cumulative effects of the taste shocks are huge. It is also worth noting that the Fisher and SV indices do not depart from the Jevons index even if they are the chained indices. That is, chain drifts of the face mask are not serious even if we use scanner data.

Figure 7: The Level of Chained Price Indices



Notes: The levels were obtained by taking the cumulative logged weekly changes of the chained indices. The indices are normalized to 100 in the first week of 2018.

6. Conclusion

This study considers the movement of prices when Japan was under a serious threat by the COVID-19 pandemic. We found that the demand shock that occurred during the period was large, which makes the Laspeyres index to be smaller than the Paasche index. The demand shocks measured by the changes in the taste parameters for the CES utility function created a large "bias" in the superlative indices such as the Fisher index as well as the SV index. While the Sato-Vartia and Fisher indices declined in early May 2020, the CCV increased, reflecting demand shock. When taste parameters change to a large extent, the CCV will capture the changes in the cost of living more than the traditional superlative indices.

This study has several limitations. When the demand for face masks surged, face masks were rationed, which makes the construction of the COLI complicated. If we could identify a product that was not rationed during the sample period, it could be possible to adopt the method developed by Tobie and Houthakker (1950-1951) and Neary and Roberts (1980) to construct the cost of living under rationing. However, as long as we use scanner data, the existence of rationing cannot be identified. If rationing occurs, the COLI tends to be greater than the index without rationing. Therefore, our estimates of the cost of living in this study should be regarded as a lower bound. Second, although the CCV allows for variable taste parameters, we need to assume that the elasticity of substitution is constant over time, which is a restrictive assumption when strong demand shock occurred. Although we could assume some form of stochastic processes for the elasticity of substitution and conduct estimations, we have not been able to obtain stable and robust estimates. Finally, we have not discussed the variety of effects developed by Feenstra (1994) and Redding and Weinstein (2020) on the COLI. Appendix B reports some results of the various effects; however, we have obtained unreasonably large negative variety effects on the COLI. Investigations of the effects of rationing, variable elasticities over time, and the effects of changing variety will be our next tasks.

7 . References

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Appendix A: Derivation of (4)

The demand function generated by equation (5) can be written in terms of the expenditure share as follows,

$$\ln w_{it} = (\sigma - 1)(\ln P_t + \ln \varphi_{it} - \ln p_{it}), \tag{A1}$$

where $\ln P_t = \ln C(p_t; \varphi_t)$.

$(A1)$ can be rewritten as

$$\ln \varphi_{it} = \frac{1}{\sigma - 1} \ln\left(\frac{w_{it}}{w_{1t}}\right) + \ln\left(\frac{p_{it}}{p_{1t}}\right) + \ln \varphi_{1t}.$$

Combined with the normalization condition in equation (6), we can obtain equation (4).

Appendix B: The Variety Effects

During the COVID-19 pandemic, due to the increasing demand for face masks, the variety of masks changed over time. One method of quantifying the effects of the changes in the product variety on the price index is provided by Feenstra (1994). Redding and Weinstein (2020) also consider a case in which the variety of commodities varies over time. This is the second CUPI in their paper. The RW index, which is the COLI when the product variety changes, is defined as follows,

$$\ln RW\left(p_s, q_s, p_t, q_t\right) = \ln CCV\left(p_s, q_s, p_t, q_t\right) + \frac{1}{\sigma - 1}\left(\ln\left(\lambda^s{}_t\right) - \ln\left(\lambda^t{}_s\right)\right), \quad \text{(A2)}$$

where $\lambda^s{}_t$ is the ratio of the expenditure share of common products in the periods t and s to the total expenditure at time t,

$$\lambda_t^s = \frac{\sum_{i \in C_{t,s}} p_{i,r} x_{i,r}}{\sum_{i \in I_t} p_{i,r} x_{i,r}} \quad \text{(A3)}$$

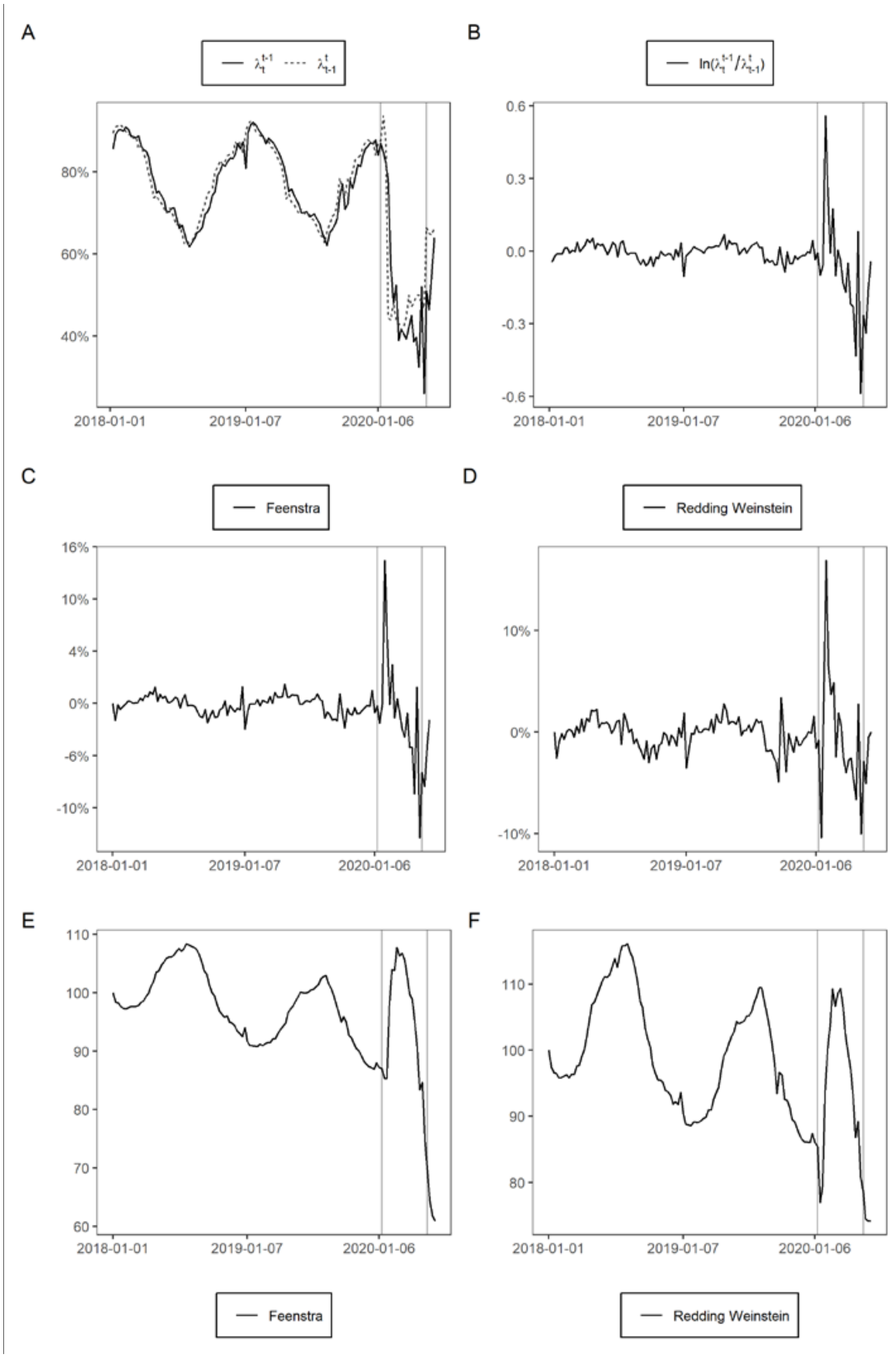
I_t : The set of all the commodities at time t.

$C_{t,s}$: The set of the common commodities at time t and s.

The second term in the right-hand side of equation (A2) is called the log λ ratio. Note that if we replace $\ln RW$ in equation (A2) with the SV, then $\ln RW$ becomes the price index by Feenstra (1994).

The movements of λ, the log λ ratio, Feenstra's index, and RW index are reported in the Appendix. As is clear from the figure, the magnitudes of the various effects during the COVID-19 period are extremely large. We suspect that this occurs due to the product turnover of identical products. Suppose a face mask A was sold at store X. Then, next week, mask A did not appear in the store due to the huge demand for the mask. Two weeks later, the mask A returned to the store X. Although this turnover is not related to the introduction of the new product, the log λ ratio is interpreted as the introduction of new products, thus affecting the cost of living index.

Appendix Figure: Variety Effects



Appendix Table: Index Numbers

date	Jevons	Fisher	Tornqvist	Sato-Vartia	CCV	date	Jevons	Fisher	Tornqvist	Sato-Vartia	CCV
2019/1/7	-0.161	-0.300	-0.299	-0.312	-1.360	2020/1/6	-0.202	-0.173	-0.167	-0.166	-0.887
2019/1/14	-0.257	-0.383	-0.373	-0.376	-1.231	2020/1/13	-0.105	-0.107	-0.107	-0.098	-0.603
2019/1/21	0.060	0.154	0.161	0.162	0.096	2020/1/20	0.119	0.179	0.204	0.166	-8.366
2019/1/28	-0.043	-0.118	-0.116	-0.106	-0.279	2020/1/27	0.684	1.095	1.083	1.085	4.212
2019/2/4	-0.268	-0.433	-0.430	-0.428	0.229	2020/2/3	1.004	2.049	2.133	2.215	5.448
2019/2/11	-0.043	0.121	0.115	0.113	-0.240	2020/2/10	0.233	0.907	0.722	0.734	1.100
2019/2/18	-0.250	-0.375	-0.371	-0.374	-0.171	2020/2/17	0.109	0.034	0.034	0.052	3.875
2019/2/25	0.242	0.250	0.268	0.278	0.271	2020/2/24	0.122	0.056	0.046	0.119	1.273
2019/3/4	0.250	0.366	0.361	0.364	0.519	2020/3/2	0.572	0.663	0.656	0.702	-0.328
2019/3/11	-0.054	-0.102	-0.110	-0.110	0.036	2020/3/9	0.344	0.313	0.310	0.346	1.786
2019/3/18	0.124	0.268	0.272	0.272	0.885	2020/3/16	-0.165	-0.339	-0.353	-0.316	1.376
2019/3/25	-0.179	-0.283	-0.280	-0.287	-0.377	2020/3/23	0.264	0.232	0.219	0.250	0.184
2019/4/1	0.656	0.696	0.699	0.715	1.437	2020/3/30	0.189	0.275	0.339	0.277	-0.502
2019/4/8	-0.093	0.131	0.134	0.135	0.523	2020/4/6	-0.004	0.066	0.028	0.076	-1.724
2019/4/15	0.157	0.185	0.187	0.185	0.528	2020/4/13	0.332	0.277	0.288	0.254	1.921
2019/4/22	-0.119	-0.198	-0.176	-0.179	1.970	2020/4/20	0.151	0.476	0.515	0.466	0.012
2019/4/29	0.333	0.453	0.441	0.445	0.710	2020/4/27	0.301	0.244	0.234	0.236	2.282
2019/5/6	0.410	0.445	0.449	0.444	0.630	2020/5/4	0.074	-0.230	-0.220	-0.117	1.128
2019/5/13	-0.117	-0.330	-0.311	-0.283	0.158	2020/5/11	0.137	-0.757	-0.730	-0.776	2.045
2019/5/20	0.019	0.311	0.286	0.251	0.415	2020/5/18	-0.112	-1.110	-1.087	-1.171	2.591
2019/5/27	-0.073	0.095	0.080	0.102	0.115	2020/5/25	-0.345	-0.938	-0.944	-0.982	1.900
2019/6/3	0.244	0.131	0.145	0.136	0.898	2020/6/1	-0.232	-0.599	-0.606	-0.612	2.773
2019/6/10	0.010	0.204	0.200	0.200	-0.014	2020/6/8	-0.258	-0.692	-0.684	-0.700	0.920
2019/6/17	-0.109	-0.084	-0.086	-0.081	0.138						
2019/6/24	0.065	-0.341	-0.235	-0.088	-0.086						
2019/7/1	0.271	0.686	0.588	0.445	0.877						
2019/7/8	-0.142	-0.092	-0.094	-0.089	-0.189						
2019/7/15	-0.131	-0.103	-0.093	-0.092	0.157						
2019/7/22	-0.077	-0.243	-0.212	-0.188	0.616						
2019/7/29	0.037	0.225	0.204	0.169	0.193						
2019/8/5	0.117	0.046	0.064	0.101	0.804						
2019/8/12	-0.157	-0.074	-0.100	-0.120	-0.338						
2019/8/19	-0.224	-0.402	-0.370	-0.367	-0.822						
2019/8/26	-0.359	-0.161	-0.167	-0.151	-1.176						
2019/9/2	-0.116	-0.111	-0.115	-0.114	-0.771						
2019/9/9	-0.468	-0.830	-0.828	-0.821	-1.703						
2019/9/16	-0.317	-0.300	-0.297	-0.295	-1.775						
2019/9/23	-0.407	-0.533	-0.530	-0.524	-3.745						
2019/9/30	0.151	0.548	0.548	0.556	3.024						
2019/10/7	-0.254	-0.069	-0.075	-0.070	0.467						
2019/10/14	-0.299	-0.627	-0.617	-0.597	-2.142						
2019/10/21	-0.287	-0.456	-0.426	-0.431	-0.102						
2019/10/28	0.000	0.092	0.080	0.079	-0.090						
2019/11/4	-0.187	-0.002	-0.005	-0.004	-0.889						
2019/11/11	-0.040	-0.028	-0.028	-0.022	-0.017						
2019/11/18	-0.299	-0.320	-0.321	-0.316	-0.589						
2019/11/25	-0.049	-0.446	-0.453	-0.474	-0.713						
2019/12/2	-0.329	-0.299	-0.293	-0.275	-0.304						
2019/12/9	-0.091	-0.076	-0.081	-0.091	-0.025						
2019/12/16	-0.211	-0.148	-0.148	-0.151	0.086						
2019/12/23	-0.054	-0.119	-0.116	-0.115	0.069						
2019/12/30	0.119	0.314	0.301	0.313	0.677						

Notes: The weekly rates of change (%) of the chained indices.