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

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We investigate the prices and quantities of face masks when the 2020 COVID-19 pandemic was particularly serious to understand the impact of demand shocks on the cost of living index (COLI). Using a recently developed index number formula that is exact for the constant elasticity of substitution utility function with variable preferences, we quantified the degree of demand shock caused by the pandemic. Our empirical analysis revealed that shifts in preferences during the pandemic were so large that the COLI with variable tastes became very different from the standard superlative indexes. While the prices of face masks decreased in the Fisher index in May 2020 by 0.76% per week, the COLI increased by 1.92% per week.

Key words: COVID-19; pandemic; coronavirus; price index; demand shocks.

1. Introduction

The coronavirus 2019 (COVID-19) pandemic promoted massive stockpiling behavior among consumers worldwide, and Japan was 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 a lockdown might be imposed, causing several people to flock to supermarkets and grocery stores to purchase food and other necessary items.

Due to the COVID-19 threat, people have changed their consumption behaviors to a large extent. Figure 1 shows the weekly rates of change of the chained Laspeyres and Paasche indexes of face masks in Japan based on scanner data. As Ivancic et al. (2011) show, weekly scanner data often exhibit large discrepancies between Laspeyres and Paasche indexes, which can be observed in the figure. In the middle of January 2020, both indexes increased to a great extent; then, the Paasche index overtook the Laspeyres index. According to the Bortkiewicz decomposition of the Laspeyres- Paasche (L-P) gap, the negative L-P 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 this period, large-

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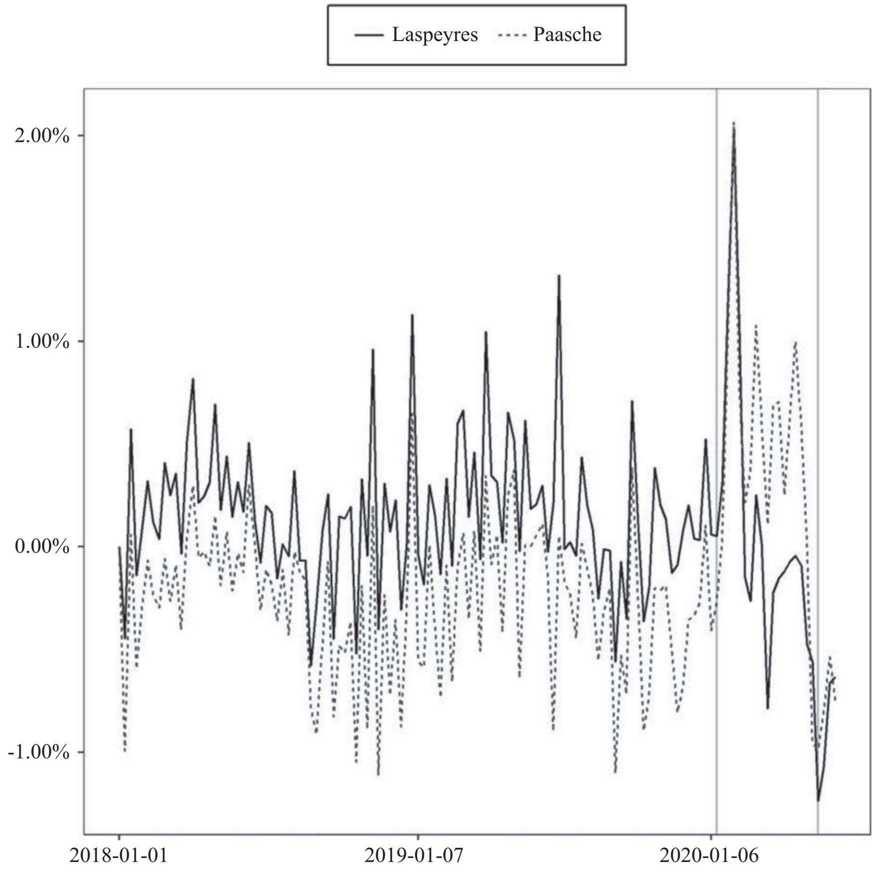

Fig. 1. Chained Laspeyres and Paasche Indexes of Face Masks.
Notes: Based on weekly Japanese scanner data. See Section 5 for the detail of the dataset.

scale demand shocks occurred, which shifted prices and quantities along an upward-sloping supply curve.

In this study, using Japanese scanner data for face masks, we investigated the impacts of demand shocks on the COLI caused by the COVID-19 in 2020. The traditional theory of COLI assumes that the preference is unchanged. Therefore, changes in demands or preferences are not captured in the COLI. One notable exception is Fisher and Shell (1972) that proposes calculating the difference between two 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 vary. Philips (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. Martin (2020) provides us with a brief survey on the cost of living index with variable preferences. In a recent path-breaking paper, Redding and Weinstein (2020) propose the constant elasticity of substitution (CES) unified price index (CUPI). The CUPI has several important characteristics. First, CUPI is exact for CES COLI without any restrictions on the relationship between quantities and prices. Second, CUPI can be decomposed into two effects; price and taste effects. Price effects can take various forms. In this study, following Redding and Weinstein (2020), we adopt the Sato-Vartia index as the price effect. Taste effects capture changes in demand or preferences. Redding and Weinstein (2020) call this effect "bias" in the traditional COLI such as the Fisher or Tornqvist indexes.

Our empirical analyses based on Japanese weekly scanner data of face masks revealed that the 2020 COVID-19 caused large-scale demand shocks. This increased the discrepancies between the traditional COLI such as the Fisher and Tornqvist indexes and CUPI to a great extent. That is, the demand shocks caused by the pandemic caused a significant change in the COLI. More specifically, while the prices of face masks decreased in the Jevons and Fisher indexes in May 2020 by 0.06% and 0.76% per week, respectively, the COLI increased by 1.92% per week. The magnitude of the changes caused by the demand shock is so substantial that traditional index numbers may carry incorrect information on the cost of living among consumers.

The article 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 describes the data set. Section 5 presents the empirical results. Section 6 concludes.

2. The 2020 COVID-19 Pandemic in Japan and Face Masks

The first COVID-19 infection was reported in Japan on January 16, 2020. From Figure 2, which depicts the change in the number of infected persons by reported date, it can be seen that the number of COVID-19 cases started to increase significantly from February 2020. In response to this pandemic, the Japanese government announced its first emergency plan on February 13. The government also requested manufacturers to increase the production of masks, which had already started to run short, and prefectures to allocate stockpiles to medical institutions. On March 10, the second emergency plan was formulated, and the resale of masks, still in short supply, was legally prohibited. In addition, the government decided to purchase 20 million reusable cloth masks in bulk to be distributed to nursing homes and nursery schools. They also decided to secure 15 million masks for medical institutions as mask imports augmented, and manufacturers were requested to increase their production.

The infection continued to spread, and the Governor of Tokyo mentioned the possibility of a lockdown at a press conference on March 23, resulting in a temporary increase in consumer demand for food and daily necessities. On April 7, a one-month state of emergency was declared in seven prefectures, including Tokyo and Osaka, and residents were requested to avoid leaving their prefectures as much as possible. The declaration was extended to all prefectures on April 16, and the period was extended to May 31. However, as the number of infected persons began to decrease in May, the declaration was lifted in 39 out of 43 prefectures on May 14, followed by three more prefectures on May 21. In response to chronic mask shortages, two reusable cloth masks were distributed during

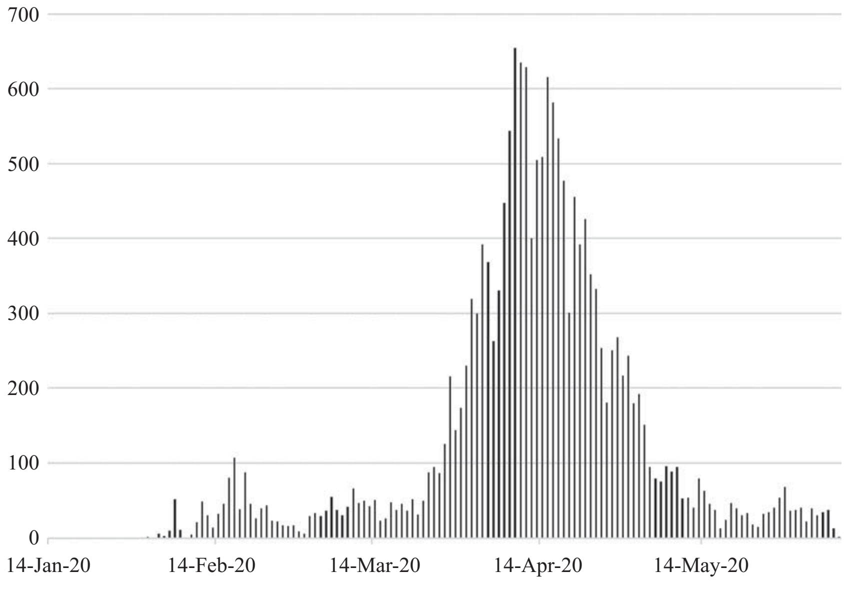

Fig. 2. Number of COVID-19 Infections in Japan.
Source: The National Institute of Infectious Diseases, Japan.

the state of emergency to each child, student, faculty, and staff member attending or working at schools, in addition to two masks to each household nationwide. These distributions were completed on June 20.

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

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

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

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

$$w_{it} = p_{it}q_{it} \Big/ \sum_{i=1}^{N} p_{it}q_{it}. \quad (3)$$

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

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

The taste parameter φ_{it} is also a function of prices and quantities as follows.

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

where $\varphi > 0$ is a positive constant. Please see Appendix (Subsection 7.1) for the derivation of Equation (4).

The first term on the right-hand side of the Equation (1) is the Sato-Vartia (SV) index. The second term. the taste term, captures the changes in the COLI caused by the changes in the preference parameters, φ_{it}. over time. RW shows that the CCV defined in Equations (1) and (4) is the COLI for the following utility function and the normalization condition.

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

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

where $\sigma > 1$ is the elasticity of substitution and $N > 1$ is the number of commodities. Since the above utility function is linearly homogeneous with respect to the quantities. the minimum expenditure function can be written as the product of the unit expenditure function. $C(p_t;\varphi_t)$ and utility level.

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

Here the unit expenditure function takes the following functional form.

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

A notable feature of the utility function in Equation (5) is that the taste parameter, φ_{it}, can vary over time. The COLI corresponding to Equation (1) is given by,

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

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

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

$$= \left(\frac{\sum_{i=1}^{N} \left(\frac{p_{it}}{\varphi_{it}} \right)^{1-\sigma}}{\sum_{i=1}^{N} \left(\frac{p_{is}}{\varphi_{is}} \right)^{1-\sigma}} \right)^{\frac{1}{1-\sigma}} \tag{7}$$

The important characteristics of the COLI in Equation (7) are: (A) its concavity with respect to the taste-adjusted prices, p_{it} / φ_{it}, and (B) its symmetric treatment of the taste-adjusted prices. The concavity of COLI comes from cost minimization. The symmetric treatment stems from our assumption that the differences among quantities in the utility function are represented by the taste parameter, φ_{it}. These two characteristics of the COLI imply that if the taste-adjusted prices become more heterogeneous, that is, if the taste-adjusted prices are more dispersed, the consumers benefit from the diversity, which enables them to attain the given utility level by smaller expenses. In other words, if the taste-adjusted prices become more dispersed, the COLI becomes smaller. Please note that this result comes not from the assumption of the CES preferences but from the equal treatments of the taste-adjusted prices. 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.

While the CCV by RW enables us to construct the COLI with variable tastes, there are several issues to be considered. First, we could not identify one of the taste parameters, φ_t, from data. For example, assume that we multiply all the taste parameters φ_t by a constant, say $\kappa > 0$, while φ_s is unchanged, since such a change is a monotonic transformation of the utility function at time t, we obtain identical demand functions at time t while the demand functions at time s are unchanged. However, the COLI will take a different value because it is a decreasing function of the taste parameters. This identification problem may seem severe because the choice of the normalization condition affects the index number. Comparing various different normalization condition, Kurtzon (2020) argues that an arbitrary choice of normalization can yield any desired CCV. Recently, Abe and Rao (2020) investigated the axiomatic properties of normalization conditions using RW. They found that the normalization condition in Equation (6) is the necessary and sufficient condition for the CCV; first to pass the commensurability test, the index number must be free from the measurement units of price and quantities, and second, to treat all the quantities equally in the normalization conditions. For example, instead of Equation (6), if we adopt the arithmetic mean, such as $(1/N)\sum_{i=1}^{N} \varphi_{it} = \varphi$, the CCV becomes sensitive to the choice of the measurement units of commodities such as pound or kilogram. Abe and Rao (2020) show that the CCV passes the transitivity test as well as the monotonicity test but fails the identity test. Therefore, in this study, we also use Equation (6) as the normalization condition.

The second issue is the interpretation of the taste term, the second term Equation (1). Martin (2020) argues that the magnitude of the taste term can be so large that the contribution of the price changes is swamped. Martin (2020) concludes that pure taste change effects are arguably out of the scope of a consumer price index and further clarifies the difference between the average price changes and the cost of living index. The CCV captures the effects of differences in taste, in addition to the effects of price changes. The taste term in the CCV reflects a strict concavity in the expenditure function. If the expenditure function is linear, that is, if σ is infinite, the taste term disappears from Equation (1). As RW shows, it is not difficult to generalize the assumption of CES preferences to a more general class of utility functions, such as Translog preferences. That is, the CCV can be regarded as the simplest case of the COLI with demand shocks, which provides us with information on the impact of demand shocks on economic welfare.

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

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

Using Equations (4) and (6), we can estimate the taste parameter, φ_{it}, from the data of the expenditure shares and prices at time t. That is, we can observe changes in taste parameters over time. A natural measure of the degree of the demand shock at time t is the root mean square deviation (RMSD), such as,

$$RMSD_t = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\ln\,\varphi_{it} - \ln\,\varphi_{it-1})^2}. \tag{8}$$

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

It is worth noting that to show the equivalence between the Sato-Vartia index and the COLI for the CES utility function, the taste parameters must be fixed over time. That is, the Sato-Vartia index or other superlative indexes become COLI only when the preferences are constant over time. In other words, the observed prices and quantities must always be on the time-invariant demand function, which is a strong assumption, particularly for the COVID-19 pandemic period in 2020. Using the CCV, we can construct the cost of living index without assuming constant demand curves.

4. Data

In this study, we used the scanner data of face masks provided by Intage Holdings Inc. The data set contains barcode level weekly sales and quantity information from nationwide retail stores in Japan. The scanner data provided by Intage is the largest point of sales data in Japan collected from more than 3,000 retail stores such as general merchandise stores, supermarkets, convenience stores, and drug stores all over Japan. Moreover, the retailers were chosen to get a nationally representative sample. We chose data for face masks between the week starting January 1, 2018, and the week starting June 8, 2020. Price information is obtained by dividing the weekly total sales at each store and the barcode by the quantities sold. When constructing such unit values, we must choose the data frequency. RW uses quarterly unit values while Diewert (2018) adopts a monthly frequency. Comparing price index numbers based on the unit values at various frequencies, Bradley (2005) found that a monthly unit value would lead to an upward bias in the cereal price index because of the aggregation of transactions at different prices. To mitigate the problems of using the unit values, we chose the weekly store-barcode level unit value, which were the finest data available. Although Japanese article number (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 article, as the commodity identifier, we use the combination of both JAN and sequential codes. The total number of commodities x stores is about 47,000.

The general movements of the total sales of face masks are shown in Figure 3. In the week starting January 13, 2020, the demand for face masks surged. The period of the 2020 COVID-19 pandemic was set as the period between the week starting January 13, 2020, and the week starting May 18, 2020. This period is illustrated as the interval between the two vertical gray lines in Figure 3. The impact of the pandemic on the sales of face masks is clear in the figure. A surge in sales appeared in the week starting from January 13.

Table 1 reports the descriptive statistics for each weekly aggregated variable. As shown in the first row, the maximum value of total sales is enormous compared to the 95th percentile point. This distortion of sales distribution mainly appeared in the week when the demand for masks increased sharply in January 2020. In the second to the fifth row, we report the mean and standard deviation of the log change in prices and expenditure share in the common product calculated per week. The table shows that changes in expenditure shares are more volatile than changes in prices.

To see the changes in variables during the COVID-19 pandemic, we conducted the following regression.

$$y_t = \alpha + \beta D_t \sum\nolimits_{i=2}^{12} \lambda_i M_t^i + \delta t.$$

The second term on the right-hand side, D_t, is a dummy variable that is set to unity during the 2020 COVID-19. The third term controls seasonality by the dummy variables, M_t^i, which represents the months from February to December. The fourth term represents the trend term. We use multiple variables as dependent variables to examine their changes during the COVID-19.

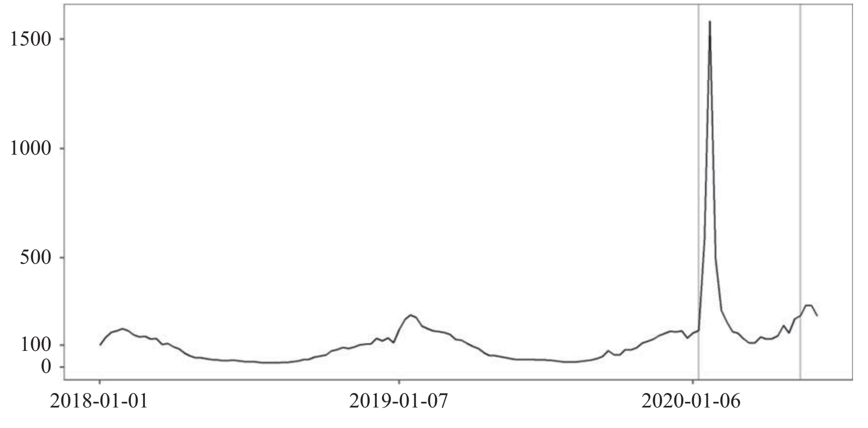

Fig. 3. Movements of the Total Sales of Face Masks.
Notes: Source: Scanner data provided by Image. The total sales in the first week of 2018 are normalized as 100.

Table 1. 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	1.00
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)	0.80	0.16	0.69	0.70	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 approximately 3,000 retail stores all over Japan.

Table 2. Changes in variables during the COVID-19.

Dependent variable	Constant	Changes after the outbreak
ln(Sales)	4.90	0.615
	[4.69, 5.10]	[0.137, 1.090]
Mean ln Δp_{it} (%)	−0.0794	0.113
	[−0.183, 0.0245]	[−0.090, 0.315]
Std. dev. ln Δp_{it}	0.0708	−0.0164
	[0.0563, 0.0853]	[−0.0238, −0.0090]
Std. dev ln Δw_{it}	0.630	0.371
	[0.502, 0.758]	[0.302, 0.440]
L-P gap (%)	0.530	−0.772
	[0.290, 0.770]	[−1.110, −0.433]

Notes: Table 2 shows the results of regression analysis that measures the change in statistics during the COVID-19 outbreak. The seasonality and trend changes were controlled using monthly dummies and a trend term. In brackets, we report 95% confidence intervals estimated by heteroskedasticity and autocorrelation consistent standard errors. The first column shows the statistics used as dependent variables. L-P Gap is the difference between the logarithms of the chained Laspeyres and Paasche indexes. The second column shows the estimated value of the constant term in January. The third column shows the estimated coefficients of the dummy variables after January 13, 2020, that is after the outbreak.

The results of the regression analysis are shown in Table 2. The sales of face masks increased by 61.5% during the 2020 COVID-19. The arithmetic mean of price changes did not show a statistically significant change and the standard deviation of price changes fell. Contrary to price changes, the standard deviation of the change in expenditure share increased during the disaster. As shown in Figure 2, the L-P gap decreased significantly.

Figure 4 reports the RMSD of the changes in logged prices and logged expenditure shares. During the first week of the 2020 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 during the first week of the COVID-19 pandemic.

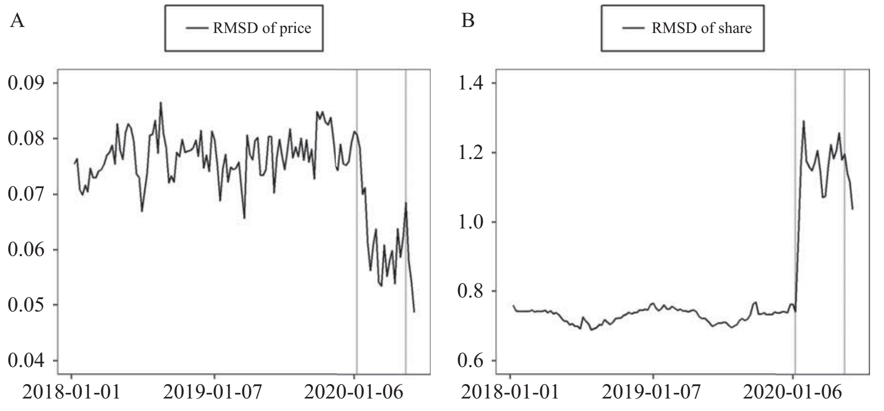

Fig. 4. Movements of the RMSD of prices and shares of face masks in Japan.
Notes: Source: Scanner data provided by Intage.

5. Empirical Results

Figure 5 shows the weekly change rates of several chained price indexes including the CCV. Panel A shows the movements of the simple geometric average price, the Jevons index, which is known to be free from chain drift. Panels B and C report the movements of the Fisher and SV indexes, respectively. The Fisher and SV indexes were 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 indexes exhibited a sharp increase in the first week of the COVID-19 period. However, when we consider changes in preferences, the movements of prices become very different. The CCV shows a sharp drop in prices during the first week of the COVID-19 pandemic, which then increased substantially. 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 elasticity of substitution is constant over time. The considerations of variable elasticity will be our future tasks. Table 3 reports the movements of the indexes including changes in sales during January-February, 2020. Appendix Table reports the index numbers of the entire sample periods. In the week starting from January 20, the sales of face masks surged, and an over 50% increase from the previous week was recorded. However, traditional price indexes, such as the Fisher price index changed little from the previous week. The CCV dropped by 8.37% in the week when the sales of face masks surged.

Figure 6 shows the movement of the RMSD of the taste parameters (Panel A) and the taste shock defined as $\sum_{i=1}^{N} \omega_{ist}^{*}(\ln \varphi_{is} - \ln \varphi_{it})$ (Panel B). First, 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 assumption of the constant taste parameters is violated. From the figure, we can also observe that in January 2020, large negative taste

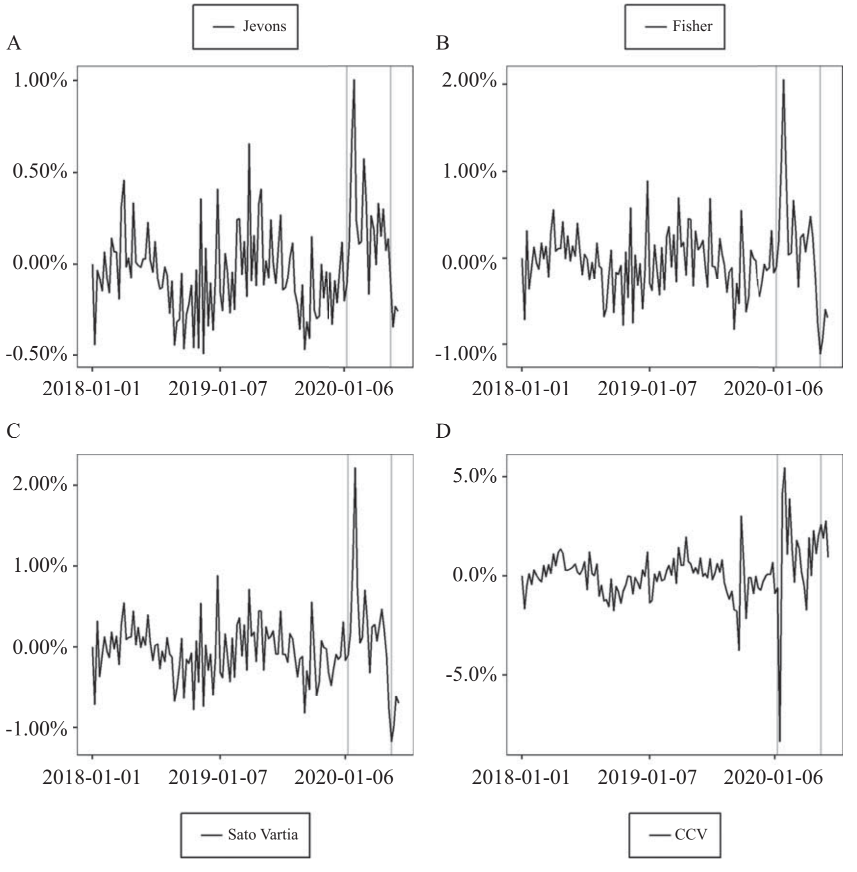

Fig. 5. Weekly change rates of several price indexes of face masks.
Notes: Weekly change rates of chained indexes. CCV stands for CES common variety price index defined in Equation (1).

Table 3. Comparisons of price indexes.

	Sales	Jevons	Fisher	Sato Vartia	CCV
2020/1/13	2.97	−0.11	−0.11	−0.10	−0.60
2020/1/20	53.92	0.12	0.18	0.17	−8.37
2020/1/27	43.46	0.68	1.09	1.08	4.21
2020/2/3	−50.59	1.00	2.05	2.22	5.45
2020/2/10	−27.88	0.23	0.91	0.73	1.10
2020/2/17	−9.90	0.11	0.03	0.05	3.87
2020/2/24	−10.38	0.12	0.06	0.12	1.27
Average. May, 2018	−2.93	0.00	0.09	0.10	0.33
May, 2019	−3.52	0.06	0.13	0.13	0.33
May, 2020	4.29	−0.06	−0.76	−0.76	1.92

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

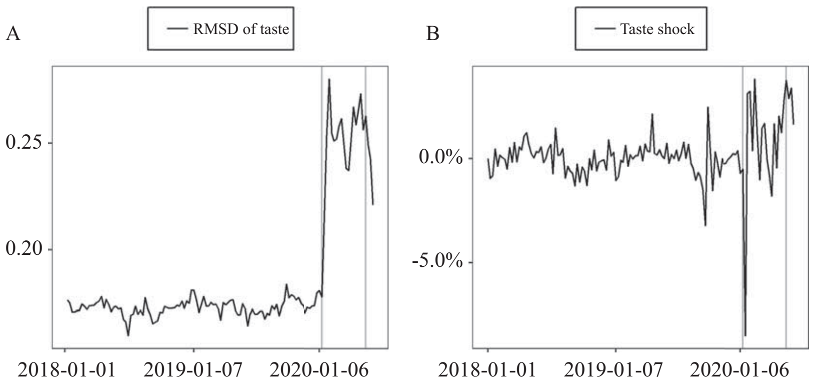

Fig. 6. The RMSD of Taste Parameters and the Taste Shock.
Notes: The RMSD of taste is defined in (8), while the taste shock is defined as the second term of the R.H.S. of (1)

shocks with a surge in the RMSD occurred, which makes the CCV drop to a great extent. The intuition behind the decline the CCV is as follows. As Equation (7) indicates, the CCV is a concave and symmetric function of the taste-adjusted prices, p_{it}/φ_{it}. This implies that people can obtain greater utility when taste-adjusted prices are more dispersed. Before the pandemic, some face masks were more popular than others, regardless of the price, which was represented as variations in the taste parameters among commodities. When people realized that face masks are effective in avoiding COVID-19 infections, their evaluation of each face mask changed to a great extent, which led to greater variations in the taste-adjusted prices than before the pandemic. The greater the dispersion, the more CCV dropped as discussed in Section 4. Opposite effects were observed in May 2020. As Table 3 shows, the CCV became positive while the standard price indexes were negative. At that time, the RMSD of tastes began to decrease, which led to smaller dispersions in the taste-adjusted prices, thus, resulting in positive taste effects.

Finally, Figure 7 shows the levels of several price indexes. In the figure, the chained Fisher and SV indexes do not depart from the Jevons index much, which suggests that chain drifts of the face mask are not serious. The deep trough of the CCV in January 2020 disappeared within a few weeks. The Jevons, Fisher, and SV indexes became smaller after the pandemic, while the CCV continued to increase. In early June 2020, the Jevons, Fisher, and SV indexes were around 97, while the CCV was more than 115. In other words, the magnitude of the cumulative effects of taste shocks was large.

6. Conclusion

By investigating the prices and quantities of face masks in Japan during the serious threat of the COVID-19 pandemic in 2020, we considered the impact of demand shocks on the COLI. We found that the demand shock that occurred during this 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 large taste effects that are not captured in the Sato-Vartia or superlative indexes such as the Fisher index. While the prices of face masks decreased in the Jevons and Fisher indexes in

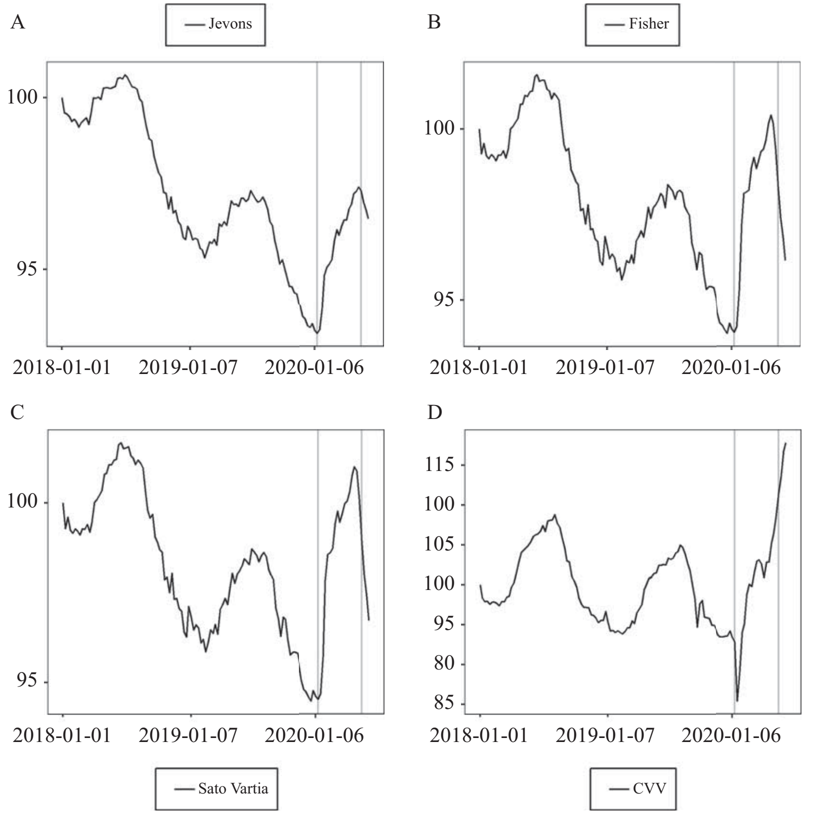

Fig. 7. Level of chained price indexes.
Notes: The levels were obtained by taking the cumulative logged weekly changes in the chained indexes. The indexes were normalized to 100 in the first week of 2018.

May 2020 by 0.06% and 0.76% per week, respectively, the COLI increased by 1.92% per week.

This study has several limitations. When the demand for face masks surged, face masks were rationed, which complicates the construction of the COLI. 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, 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 a 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 did not discuss the variety of effects developed by Feenstra (1994) and Redding and Weinstein (2020) on COLI. Appendix (Subsection 7.2) 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 task.

7. Appendix

7.1. Derivation of Equation (4)

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

$$\ln w_{it} = (\sigma - 1)(\ln P_t + \ln \varphi_{it} - \ln p_{it}), \tag{9}$$

where $\ln P_t = \ln C(p_t; \varphi_t)$.
(9) 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).

7.2. 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 wherein the variety of commodities changes 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,

$$\ln RW(p_s, q_s, p_t, q_t) = \ln CCV(p_s, q_s, p_t, q_t) + \frac{1}{\sigma - 1}(\ln(\lambda_t^s) - \ln(\lambda_s^t)). \tag{10}$$

Here, λ_t^s is the ratio of the expenditure share of common products in the periods t and s to the total expenditure at time t,

$$\lambda_t^s = \frac{\sum_{i \in C_{t,s}} p_{i,r} x_{i,r}}{\sum_{i \in I_t} p_{i,r} x_{i,r}} \tag{11}$$

I_t : Set of all commodities at time t.

$C_{t,s}$: Set of common commodities at time t and s.

The second term on the right-hand side of Equation (10) is called the log λ ratio. Note that if we replace ln RW in Equation (10) with 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 because of the product turnover of the identical products. Suppose face mask A was sold at store X. Then, the next week, mask A did not appear in the store because of the huge demand for the mask. Two weeks later, mask A returned to 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.

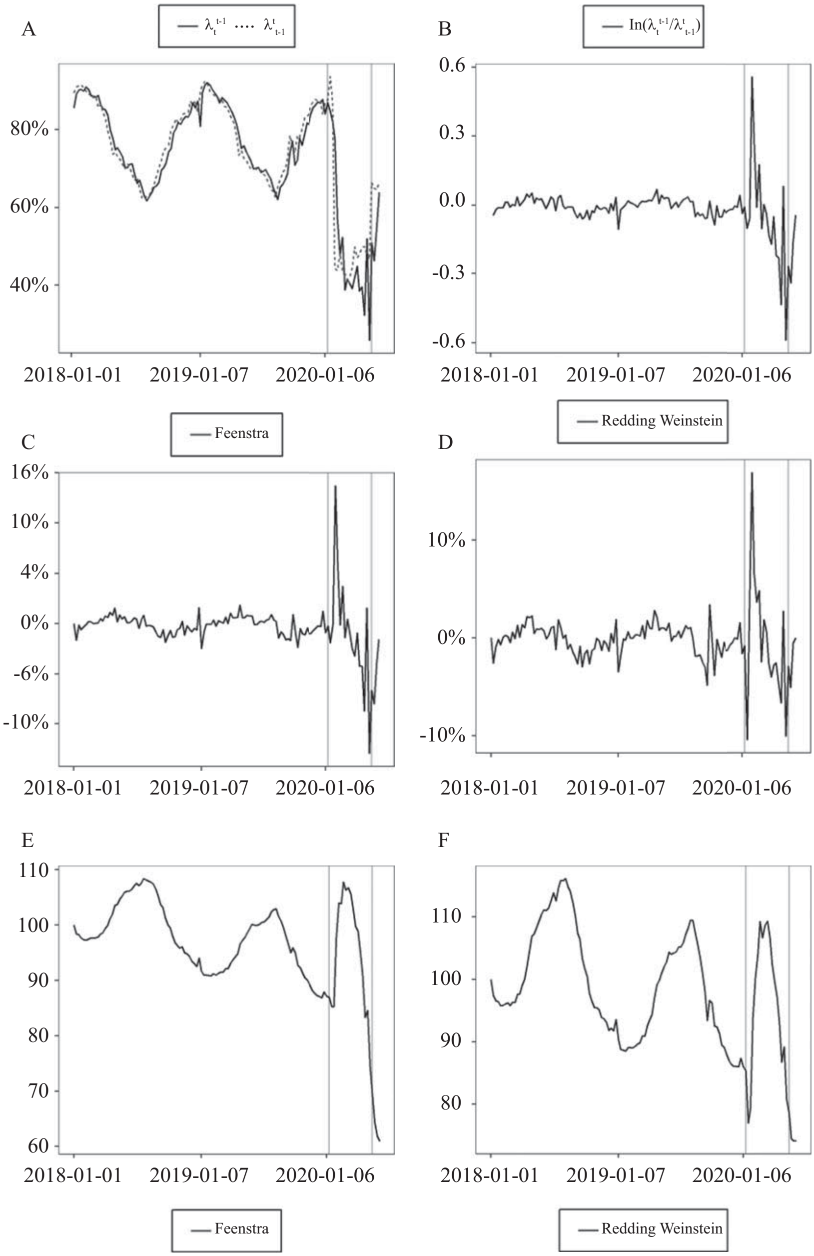

Fig. 8. Variety Effects

Table 4. Index numbers

	Sales	Jevons	Fisher	Sato-Vartia	CCV		Sales	Jevons	Fisher	Sato-Vartia	CCV
2019/1/7	0.190	-0.002	-0.003	-0.003	-0.014	2020/1/6	0.073	-0.002	-0.002	-0.002	-0.009
2019/1/14	0.100	-0.003	-0.004	-0.004	-0.012	2020/1/13	0.030	-0.001	-0.001	-0.001	-0.006
2019/1/21	0.039	0.001	0.002	0.002	0.001	2020/1/20	0.539	0.001	0.002	0.002	-0.084
2019/1/28	-0.021	0.000	-0.001	-0.001	-0.003	2020/1/27	0.435	0.007	0.011	0.011	0.042
2019/2/4	-0.084	-0.003	-0.004	-0.004	0.002	2020/2/3	-0.506	0.010	0.020	0.022	0.054
2019/2/11	-0.026	0.000	0.001	0.001	-0.002	2020/2/10	-0.279	0.002	0.009	0.007	0.011
2019/2/18	-0.026	-0.003	-0.004	-0.004	-0.002	2020/2/17	-0.099	0.001	0.000	0.001	0.039
2019/2/25	-0.007	0.002	0.002	0.003	0.003	2020/2/24	-0.104	0.001	0.001	0.001	0.013
2019/3/4	-0.015	0.003	0.004	0.004	0.005	2020/3/2	-0.023	0.006	0.007	0.007	-0.003
2019/3/11	-0.022	-0.001	-0.001	-0.001	0.000	2020/3/9	-0.082	0.003	0.003	0.003	0.018
2019/3/18	-0.072	0.001	0.003	0.003	0.009	2020/3/16	-0.066	-0.002	-0.003	-0.003	0.014
2019/3/25	-0.014	-0.002	-0.003	-0.003	-0.004	2020/3/23	0.009	0.003	0.002	0.002	0.002
2019/4/1	-0.055	0.007	0.007	0.007	0.014	2020/3/30	0.091	0.002	0.003	0.003	-0.005
2019/4/8	-0.058	-0.001	0.001	0.001	0.005	2020/4/6	-0.031	0.000	0.001	0.001	-0.017
2019/4/15	-0.041	0.002	0.002	0.002	0.005	2020/4/13	0.006	0.003	0.003	0.003	0.019
2019/4/22	-0.123	-0.001	-0.002	-0.002	0.020	2020/4/20	0.038	0.002	0.005	0.005	0.000
2019/4/29	-0.087	0.003	0.005	0.004	0.007	2020/4/27	0.126	0.003	0.002	0.002	0.023
2019/5/6	-0.003	0.004	0.004	0.004	0.006	2020/5/4	-0.087	0.001	-0.002	-0.001	0.011
2019/5/13	-0.052	-0.001	-0.003	-0.003	0.002	2020/5/11	0.151	0.001	-0.008	-0.008	0.020
2019/5/20	-0.048	0.000	0.003	0.003	0.004	2020/5/18	0.029	-0.001	-0.011	-0.012	0.026
2019/5/27	-0.038	-0.001	0.001	0.001	0.001	2020/5/25	0.079	-0.003	-0.009	-0.010	0.019
2019/6/3	-0.043	0.002	0.001	0.001	0.009	2020/6/1	-0.001	-0.002	-0.006	-0.006	0.028
2019/6/10	0.016	0.000	0.002	0.002	0.000	2020/6/8	-0.082	-0.003	-0.007	-0.007	0.009
2019/6/17	-0.011	-0.001	-0.001	-0.001	0.001						
2019/6/24	-0.017	0.001	-0.003	-0.001	-0.001						
2019/7/1	-0.011	0.003	0.007	0.004	0.009						
2019/7/8	-0.003	-0.001	-0.001	-0.001	-0.002						
2019/7/15	-0.025	-0.001	-0.001	-0.001	0.002						
2019/7/22	-0.055	-0.001	-0.002	-0.002	0.006						
2019/7/29	-0.037	0.000	0.002	0.002	0.002						
2019/8/5	-0.038	0.001	0.000	0.001	0.008						
2019/8/12	-0.005	-0.002	-0.001	-0.001	-0.003						
2019/8/19	0.059	-0.002	-0.004	-0.004	-0.008						
2019/8/26	0.055	-0.004	-0.002	-0.002	-0.012						
2019/9/2	0.054	-0.001	-0.001	-0.001	-0.008						
2019/9/9	0.062	-0.005	-0.008	-0.008	-0.017						
2019/9/16	0.108	-0.003	-0.003	-0.003	-0.018						
2019/9/23	0.184	-0.004	-0.005	-0.005	-0.037						
2019/9/30	-0.123	0.002	0.005	0.006	0.030						
2019/10/7	-0.008	-0.003	-0.001	-0.001	0.005						
2019/10/14	0.157	-0.003	-0.006	-0.006	-0.021						
2019/10/21	-0.009	-0.003	-0.005	-0.004	-0.001						
2019/10/28	0.055	0.000	0.001	0.001	-0.001						
2019/11/4	0.091	-0.002	0.000	0.000	-0.009						
2019/11/11	0.033	0.000	0.000	0.000	0.000						
2019/11/18	0.033	-0.003	-0.003	-0.003	-0.006						
2019/11/25	0.051	0.000	-0.004	-0.005	-0.007						
2019/12/2	0.028	-0.003	-0.003	-0.003	-0.003						
2019/12/9	0.028	-0.001	-0.001	-0.001	0.000						
2019/12/16	-0.009	-0.002	-0.001	-0.002	0.001						
2019/12/23	0.012	-0.001	-0.001	-0.001	0.001						
2019/12/30	-0.096	0.001	0.003	0.003	0.007						

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

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