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Effects of the State of Emergency during the COVID-19 Pandemic on Tokyo Vegetable Markets

Kentaka Aruga [1,*], Md. Monirul Islam [2,3] and Arifa Jannat [3,4]

1 Graduate School of Humanities and Social Sciences, Saitama University, 255 Shimo-Okubo, Sakura-ku, Saitama 338-8570, Japan
2 Department of Agricultural Economics, Bangladesh Agricultural University, Mymensingh 2202, Bangladesh
3 Graduate School of Life and Environmental Sciences, University of Tsukuba, Tsukuba 305-8572, Japan
4 Institute of Agribusiness and Development Studies, Bangladesh Agricultural University, Mymensingh 2202, Bangladesh
* Correspondence: aruga@mail.saitama-u.ac.jp

Abstract: The state of emergency (SOE) period in Tokyo under the COVID-19 pandemic restricted people to staying in their homes and changed human mobility, which has impacted the major agricultural markets in Tokyo. In this research, we analyzed how the changes in people's staying-at-home behaviors during the four SOE periods (7 April 2020–28 October 2021) in Tokyo affected the daily market prices of cabbage, tomato, Japanese radish, carrot, and potato. Using the autoregressive distributed lag (ARDL) model, the study reveals that all the investigated vegetables except potatoes have a long-term relationship with the staying-at-home index. The long-term influence of staying-at-home behaviors on cabbage, tomato, radish, and carrot markets during the early SOE periods had a negative impact on these vegetable prices, indicating that an increase in the hours of staying-at-home as related to SOE measures might have decreased the demand for these vegetables. The negative impact of the stay-at-home index on vegetable prices lessened in the fourth SOE period, likely because more people did not remain in their homes. Moreover, the study findings reveal that, compared to less perishable vegetables, the price of perishable vegetables is more likely to have been affected by human mobility constraints during the pandemic. Therefore, agricultural policymakers should consider providing subsidies to producers based on the negative influence on market prices of perishable and less perishable vegetables in pandemic situations, such as COVID-19.

Keywords: vegetable price; state of emergency; stay-at-home; ARDL; COVID-19

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1. Introduction

Lockdown regulations in many countries prohibited people from leaving their homes unless they needed to buy daily necessities [1]. Preliminary descriptive studies have shown a significant decrease in country-level physical activity because of the stay-at-home recommendations and strict lockdown measures [2]. Even going to public parks was restricted in some countries where the implementation of social distancing was challenging. The decline in human mobility during COVID-19 has disturbed the marketing system of primary agricultural products [3], and this stagnant mobility might hurt logistics systems and cause disruptions in the food supply chain globally [4,5].

Supply chains for agriculture commodities encompass all activities from farm to fork, including production, packaging, distribution, storing, and consumption [6]. Any disruption in the flow of agricultural products and services can be economically disastrous since it is a critical component of a network of organizations and people involved in distribution. In agriculture, a disruption to the supply chain refers to an interruption in the flow of products or services between production and the end consumer [7]. According to previous studies [4,6,8], pandemic outbreaks influence the food supply chains in four distinct ways in both developed and developing nations: food prices, food supply, food demand, and food transportation.

Even though the Japanese state of emergency (SOE) rules were not as strict as those in other countries, human mobility decreased after their implementation. According to Tokyo Shoko Research, 842 restaurants filed for bankruptcy in 2020, up 5.3% from the previous year, with at least 10 million JPY in debt. The Japan Food Service Association reported that overall sales in the restaurant sector were down 17% in March and down 40% in April versus 2019 [9]. Fast food restaurants have been the least impacted due to take-out, delivery, and drive-through business, with sales dropping 15.6% in April versus last year in 2020. While a decrease in customers dining out significantly damaged Japanese and Western-style restaurants, Chinese restaurants were able to maintain 90% of regular sales, as many already offered take-out service. Although many young farmers introduced niche markets in online sales, direct sales, etc., the extent of online business has been minimal.

Moreover, the International Monetary Fund (IMF) forecasted that the global COVID-19 pandemic would hit Japan with an economic recession and a 5.3% decrease in the gross domestic product (GDP), particularly regarding substantially declining consumer spending [10]. As a result of the COVID-19 pandemic, nearly every industry connected to globalized food systems has been disrupted. The fact that Japan imports over 60% of its food (based on calories) creates pressure on its vulnerable agriculture sector, which suffers from a declining and aging farming population and low food security [11]. These economic contractions, along with the imposition of the SOE, might have impacted the market prices of major vegetables in the Japanese market. Therefore, understanding how the SOE influenced the agricultural market is an urgent and burning issue.

Thus, the study's overall goal is to investigate the effects of the SOE during the COVID-19 pandemic on the Tokyo major vegetable markets. We assume that the restrictions enforced on human mobility during the SOE have reduced the major vegetable demand, impacting market prices. Particularly, we expect that the decline in the number of people going out to restaurants during the SOE will have had an adverse impact on fresh vegetable demand leading to a price decrease. Since freshness is essential for highly perishable vegetables, we conjecture that those perishable vegetables will be more affected by the SOE compared to less perishable ones.

Numerous studies have investigated the impact of COVID-19 on various aspects, such as on South Asian economies [12], retail food prices in the United States (US) [13], and CO_2 emissions [14]. Many of these studies have also investigated the effects on agriculture. For example, Jena et al. [15] analyzed the influence on the agricultural system and food prices in India, Chen and Yang [16] examined COVID-19 effects on agricultural food sales in China, and Readon et al. [17] investigated how the food prices of agricultural commodities are affected by the COVID-19 in developing economies. Most of these studies assume that the adverse impact on food price is related to restrictions imposed by governments to limit human mobility to prevent the spread of COVID-19, but they do not include the stay-at-home restrictions as an endogenous variable in their models. Akter [18] is one of few studies that use the Stay-at-Home Restriction Index (SHRI) to evaluate the effects of human mobility restrictions on food prices. However, this study only studies the effect of the human mobility change on combined food price indices rather than testing its impact on specific food prices. Thus, no studies have yet tested how changes in human mobility during COVID-19 have impacted the individual food price. This study is the first attempted research that examines the impact of COVID-19, considering perishable and less perishable nature along with changes in human mobility during different SOE periods, on major vegetables from one of the largest metropolitan cities in Japan.

To shed light on this issue, the current study examines how the countermeasure restricting human mobility during COVID-19 has influenced the five major wholesale vegetable prices: cabbage, tomato, Japanese radish (*daikon*), carrot, and potato prices.

Understanding whether the regulations on human mobility implemented in order to slow the spread of the disease had adverse effects on vegetable market prices is an essential issue for participants in the vegetable markets and policymakers that need to cope with potential risks related to price declines related to the COVID-19 pandemic. Thus, the study results will provide imperative information for these stakeholders to prepare and deal with the negative influence vegetable markets may face when human mobility is restricted under governmental regulation.

2. Materials and Methods

The Toyosu market has been chosen as the case study because, as of July 2021, Tokyo has the highest cumulative number of COVID-19 cases among all Japanese cities, with over 37.5 million inhabitants [19], and it is the world's fourth most expensive metropolis. The major vegetables—cabbage, tomato, Japanese radish (*daikon*), carrot, and potato—were selected based on secondary data from a survey conducted in 2020 [20] as they are major vegetables of perishable (cabbage, tomato, Japanese radish) and less perishable (carrot and potato) nature [21]. The variables used in this study are described in Table 1.

Table 1. Description of variables.

Variables	Symbol	Measurement Unit	Sources
Cabbage price	CP	10 pieces (JPY)	Toyosu market [22]
Cabbage volume	CV	Kg	
Tomato price	TP	4 pieces (JPY)	
Tomato volume	TV	Kg	
Radish price	RP	10 pieces (JPY)	
Radish volume	RV	Kg	
Carrot price	CRP	10 Pieces (JPY)	
Carrot volume	CRV	Kg	
Potato price	PP	10 pieces (JPY)	
Potato volume	PV	Kg	
Residential (stay-at-home restriction index)	Home	The number of visitors to residential areas has changed compared to baseline days (the median value for the 5 weeks from 3 January to 6 February 2020). This index is smoothed to a rolling 7-day average.	Google LLC [23]
COVID-19 cases in Tokyo	TC	Daily (Number)	https://stopcovid19.metro.tokyo.lg.jp (accessed on 25 February 2022)

Moreover, depending on data availability, daily time series data covering the four SOE periods was used in this study. SOE was implemented in four phases from 7 April 2020: SOE-1 (7 April to 25 May 2020), SOE-2 (1 August 2020 to 21 March 2021), SOE-3 (24 April 2021 to 20 June 2021), and SOE-4 (12 July 2021 to 30 September 2021). Before and after the third SOE (12–24 April 2021 and 21 June–11 July 2021), a semi-SOE was implemented by the Tokyo government where the restriction on the restaurants' business hours was not as strict as the SOE (8:00 pm) but were limited to 9:00 pm. Thus, we expect that the impact of SOE on human mobility is sustained prior to and after the SOE for a certain period, and in order to capture this influence, we defined our SOE periods as the time period during the SOE restrictions and four weeks before and after the SOE. Table 2 summarizes the data range used for our SOEs:

Table 2. Data range under different SOEs.

SOEs	Starting Dates	Ending Dates	Before 4 Weeks	After 4 Weeks
1st	7 April 2020	25 May 2020	10 March 2020	22 June 2020
2nd	8 January 2021	21 March 2021	11 December 2020	17 April 2021
3rd	25 April 2021	20 June 2021	29 March 2021	17 July 2021
4th	2 July 2021	30 September 2021	14 June 2021	28 October 2021

Before employing the econometric approaches, we conducted conventional unit root tests. The study employed the Phillips–Perron (PP) [24], the augmented Dickey–Fuller

(ADF) [25], and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) [26] tests to check the stationarity. Based on the results of one of these tests, we were able to confirm that all our endogenous variables could be considered as either integrated as zero or one (I (0) or I (1)) (Table 3).

Table 3. Unit root tests.

SOE	Variables	Levels			First Differences		
		PP	ADF	KPSS	PP	ADF	KPSS
1st	CP	−2.514	−2.973	0.205 **	−7.561 ***	−7.603 ***	0.032
	CV	−7.537 ***	−4.420 ***	0.154 **	−41.412 ***	−7.315 ***	0.162 **
	TP	−2.983	−1.184	0.186 **	−15.217 ***	−14.974 ***	0.110
	TV	−10.827 ***	−2.490	0.092	−29.397 ***	−8.483 ***	0.050
	RP	−5.405 ***	−5.124 ***	0.062	−13.188 ***	−9.300 ***	0.048
	RV	−5.818 ***	−2.961 **	0.284 ***	−68.237 ***	−4.885 ***	0.175 **
	CRP	−5.327 ***	−1.658	0.202 **	−18.654 ***	−4.936 ***	0.044
	CRV	−8.585 ***	−2.672	0.234 ***	−39.507 ***	−4.959 ***	0.007
	PP	−5.356 ***	−5.315 ***	0.102	−29.271 ***	−7.162 ***	0.075
	PV	−8.039 ***	−8.041 ***	0.103	−35.333 ***	−8.146 ***	0.252 ***
	Home	−0.802	−1.134	0.262 ***	−5.137 ***	−5.107 ***	0.096
	TC	−2.738	−3.130	0.188 **	−16.59 ***	−1.471	0.178 **
2nd	CP	−3.965 **	−3.681 **	0.099	−13.483 ***	−6.886 ***	0.130 *
	CV	−8.131 ***	−8.127 ***	0.049	−65.965 ***	−8.373 ***	0.088
	TP	−7.060 ***	−2.483	0.258 ***	−35.331 ***	−7.537 ***	0.048
	TV	−9.634 ***	−9.628 ***	0.079	−37.267 ***	−5.114 ***	0.021
	RP	−3.022	−2.687	0.221 ***	−12.682 ***	−4.549 ***	0.032
	RV	−9.552 ***	−3.302 *	0.055	−19.674 ***	−7.923 ***	0.069
	CRP	−4.708 ***	−1.890	0.188 **	−17.683 ***	−11.029 ***	0.020
	CRV	−7.467 ***	−1.595	0.314 ***	−38.190 ***	−5.592 ***	0.188 **
	PP	−7.651 ***	−6.713 ***	0.217 ***	−34.202 ***	−6.183 ***	0.127 *
	PV	−8.405 ***	−8.407 ***	0.061	−35.075 ***	−7.325 ***	0.093
	Home	−3.528 **	−3.610 **	0.142 *	−12.383 ***	−8.073 ***	0.111
	TC	−3.035	−2.788	0.133 *	−11.769 ***	−2.529	0.145 *
3rd	CP	−2.993	−3.211 *	0.081	−7.768 ***	−7.744 ***	0.047
	CV	−5.222 ***	−1.749	0.247 ***	−24.693 ***	−10.538 ***	0.168 **
	TP	−5.149 ***	2.918	0.197 **	−18.165 ***	−4.891 ***	0.031
	TV	−8.773 ***	−2.541	0.100	−18.105 ***	−4.688 ***	0.058
	RP	−4.051 **	−2.490	0.106	−14.108 ***	−5.285 ***	0.056
	RV	−4.686 ***	−2.357	0.235 ***	−27.279 ***	−2.188	0.229 ***
	CRP	−5.535 ***	−5.561 ***	0.156 **	−24.510 ***	−8.155 ***	0.182 **
	CRV	−9.974 ***	−5.462 ***	0.098	−46.317 ***	−9.900 ***	0.111
	PP	−4.118 ***	−3.423 *	0.260 ***	−20.285 ***	−6.126 ***	0.095
	PV	−8.358 ***	−2.191	0.230 ***	−48.691 ***	−4.196 ***	0.099
	Home	−2.451	−2.158	0.176 **	−5.317 ***	−5.845 ***	0.033
	TC	−3.390 *	−0.627	0.179 **	−13.742 ***	−0.627	0.500 ***
4th	CP	−2.165	−1.873	0.146 **	−12.077 ***	12.077 ***	0.068
	CV	−7.977 ***	−3.600 **	0.212 **	−25.953 ***	−8.437 ***	0.094
	TP	−2.760	−1.954	0.129*	−16.117 ***	−16.753 ***	0.030
	TV	−8.194 ***	−1.631	0.231 ***	−48.256 ***	−5.033 ***	0.138 *
	RP	−5.681 ***	−3.411 *	0.083	−15.651 ***	−5.634 ***	0.049
	RV	−7.778 ***	−4.084 ***	0.239 ***	−35.492 ***	−9.030 ***	0.132 *
	CRP	−9.803 ***	−3.574 **	0.163 **	−43.892 ***	−12.969 ***	0.082
	CRV	−9.949 ***	−2.071	0.200 **	−46.269	−10.873 ***	0.453 ***
	PP	−8.186 ***	−3.396 *	0.179 **	−28.233 ***	−9.124 ***	0.085
	PV	−8.306 ***	−8.306 ***	0.285 ***	−37.750 ***	−8.980 ***	0.157 **
	Home	−2.037	−0.280	0.258 ***	−7.629 ***	−3.262 *	0.034
	TC	−1.577	−2.290	0.261 ***	−14.362 ***	−1.867	0.096

Note: All the unit root tests include both a constant and a linear trend. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. The null hypothesis of the PP and ADF tests are variables that contain unit roots, while that for the KPSS test is the stationarity of the variables.

We applied the autoregressive distributed lag (ARDL) model because it recently gained popularity in impact assessment studies [14,27]. One of the main reasons we used the ARDL model is that it is effective even when the sample size is small and can avoid omitted variables and auto-correlation issues [28]. Since the SOE effects are most likely seen regarding the number of hours spent at home, we expect that longer stays in residential areas will affect the market prices of our selected vegetables. Based on models from previous studies [14], the effects of changes in human mobility under the COVID-19 pandemic on the market prices of major vegetables were analyzed using the following equations:

$$VP = constant + \beta_1 VV + \beta_2 Home + \beta_3 TC + \varepsilon_t \quad (1)$$

where *VP* is one of the vegetable prices investigated in this study. Similarly, *VV* is the quantity of either cabbage, tomato, radish, potato, or carrot; *TC* is the daily number of COVID-19 cases in Tokyo; and ε_t is the error term. β_1, β_2, and β_3 are the coefficients of variables.

The study uses the Akaike Information Criterion (AIC) for choosing the optimal lag lengths for the ARDL models. Under the ARDL models, the bound test for cointegration is performed and the conditional error correction models are estimated in order to investigate the short-term and long-term dynamics. The ARDL (*p*, *q*, *r*) model estimation is conducted with the following unrestricted error correction model:

$$\begin{aligned}\Delta VP_t = C + \beta_1 VP_{t-1} + \beta_2 VV_{t-1} + \beta_3 Home_{t-1} + \textstyle\sum_{i=0}^{p} \beta_{4i} \Delta VP_{t-i} + \sum_{i=1}^{q} \beta_{5i} \Delta VV_{t-i} \\ + \textstyle\sum_{i=2}^{r} \beta_{6i} \Delta Home_{t-i} + \beta_7 TC + \varepsilon_t\end{aligned} \quad (2)$$

where *p* is the lag of the independent variable, and *q* and *r* are that of the dependent variables; Δ is the first difference operator; and ε_t is the error term. The error term is assumed to be white noise, normally and identically distributed.

The short-term analysis shows the impact of daily changes of COVID-19 cases on market prices of studied vegetables, while the long-term analyses represent the changes of COVID-19 cases on market prices for the entire studied period.

To test whether the models contain serial correlation and heteroskedasticity issues, the Breusch–Godfrey test for autocorrelation [29,30] and the Breusch and Pagan [31] test for heteroskedasticity were performed. The cumulative sum (CUSUM) test was also conducted to examine the stability of the parameters estimated by the ARDL model. As observable from the Breusch–Godfrey (BG) test results presented in Table 4, none of our models contained any serial correlation issues under the 5% significance level, except the tomato model under SOE-4. The Breusch–Pagan–Godfrey (BPG) test suggested that most of our models are homoscedastic, based on the 1% significance level, but the carrot (SOE-1 to SOE-3) models contained heteroscedasticity.

Table 4. Serial correlation and heteroskedasticity tests.

SOE	Model	BG F-Stat.	BPG F-Stat.	SOE	Model	BG F-Stat.	BPG F-Stat.
1st	Cabbage	0.085	2.668 **	3rd	Cabbage	0.711	0.668
	Tomato	2.803 *	1.361		Tomato	0.658	3.565 ***
	Radish	0.634	0.807		Radish	1.307	1.504
	Carrot	1.127	3.485 ***		Carrot	0.482	4.319 ***
	Potato	1.598	0.290		Potato	0.426	0.854
2nd	Cabbage	1.803	1.860 *	4th	Cabbage	0.226	1.681
	Tomato	0.184	1.530		Tomato	4.236 **	0.879
	Radish	0.549	2.119 *		Radish	1.696	1.691 *
	Carrot	1.043	2.746 ***		Carrot	0.399	2.140 **
	Potato	1.618	1.002		Potato	0.019	0.937

Note: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

To overcome the issues of serial correlation and heteroscedasticity, we used the Newey–West heteroscedasticity and autocorrelation corrected (HAC) standard errors for estimating the ARDL model coefficients. We also investigated the stability of the parameters estimated with the cumulative sum (CUSUM) test. Details of the CUSUM test results are provided in Appendix A (Figures A1–A4).

3. Results and Discussions

In this section, we will first explain the descriptive statistics of our modeled variables, i.e., five major vegetable sales volumes and daily COVID-19 cases, to obtain a general scenario of Toyosu markets during the four SOE periods. In the next step, we will explain the findings of both long-term and short-term effects of people staying at home on vegetable market prices in different SOE periods.

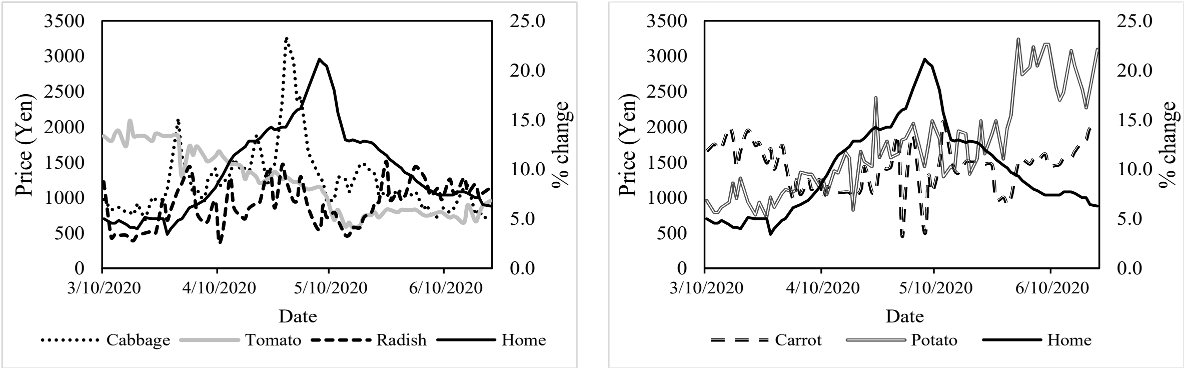
3.1. Descriptive Statistics

Table 5 illustrates the descriptive statistics of our modeled variables. It is interesting to note that for all vegetables, the volume traded in the Toyosu market is much higher in the SOE-4 compared to the SOE-1. Figure 1a–d are the plots of our modeled variables with residents' changes in staying at home during the four SOEs. Comparing the mean, median, and standard deviation of the staying at home index in Table 5, it is discernible that the numbers for the SOE-1 are much higher than the SOE-4, suggesting that more people were leaving their homes in the SOE-4. This likely indicates that the SOE measures' effect weakened as people became used to the situation, and more people did not remain in their homes in SOE-4 compared to SOE-1.

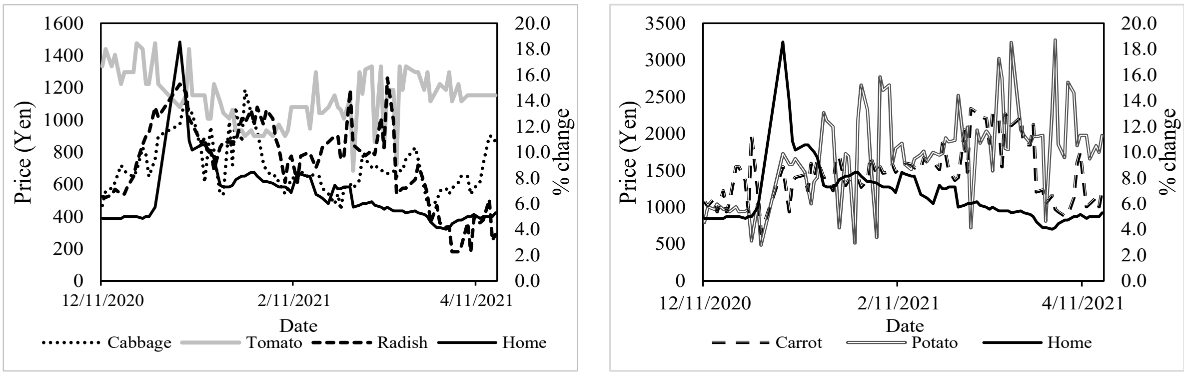
Table 5. Descriptive statistics.

SOE	Statistics	CP	CV	TP	TV	RP	RV	CRP	CRV	PP	PV	Home	TC
1st	Mean	1230.9	74,509.5	1215.8	36,446.5	907.6	20,738.3	1423.4	62,811.2	1718.9	23,965.9	9.8	56.6
	Median	1107	71,001	1215	33,838	936.0	19,528.5	1476.0	50,793.0	1566	21,964	8.8	28.5
	Maximum	3276	125,340	2088	73,050	1515.7	39,350.0	2079.0	214,271.0	3240	53,630	21.1	204
	Minimum	684	44,060	576	15076	360.0	9145.0	468.0	3864.0	720	6636	3.4	0
	Std. Dev.	495.8	18,489.8	453.7	13,285.2	311.3	6693.8	333.9	39,205.0	700.5	9688.7	4.4	59.2
	Skewness	1.99	0.59	0.275	0.741	−0.01	0.76	−0.41	1.47	0.633	0.814	0.612	1.1
	Kurtosis	7.59	2.74	1.64	3.35	1.97	3.02	3.11	5.35	2.41	3.86	2.66	3
	Jarque–Bera	114.1 ***	4.5	6.6 **	7.2 **	3.3	7.0 **	2.1	43.9 ***	6.0 **	10.5 ***	5.0 *	16.1 ***
	Obs.	74	74	74	74	74	74	74	74	74	74	74	74
2nd	Mean	703.3	75,165.7	1135.8	30,285.4	728.3	31,151.9	1486.2	52,352.9	1715.2	23,036	6.6	651
	Median	666	73,485	1152	28,497.5	780.7	30,262.5	1469.7	44,562.0	1746	21,249.5	5.9	451.5
	Maximum	1188	119,982	1476	85,952	1260.0	75,545.0	2340.0	16,6562.0	3276	80,370	18.5	2520
	Minimum	441	33,708	684	14286	180.0	12,015.0	648.0	19,896.0	486	1401	4	116
	Std. Dev.	164.1	19,726.98	168	10,884.9	257.3	9346.8	390.9	27,128.2	614.3	11,657.3	2.2	514.7
	Skewness	0.98	0.174164	−0.21	1.76	−0.32	1.48	0.40	1.93	0.12	1.51	2.25	1.92
	Kurtosis	3.53	2.38526	2.79	9.3	2.49	8.19	2.61	7.35	2.94	8.23	11.01	6.6
	Jarque–Bera	15.4 ***	1.8	0.83	191.2 ***	2.4	130.7 ***	2.9	124.0 ***	0.2	134.3 ***	310.1 ***	100.7 ***
	Obs.	88	88	88	88	88	88	88	88	88	88	88	88
3rd	Mean	731.8	78,812.7	1093.4	36,420.2	730.3	19,051.1	1099.2	53,344.8	2010.2	19,599.3	6.2	610.4
	Median	702	76,569	1116	32,783	630.0	18,165.0	1044.0	47,393.0	1980	19,700	6	563
	Maximum	1188	128,977	1836	84,185	1512.0	33,236.0	2916.0	166,562.0	3456	41,576	12.8	1411
	Minimum	450	43,238	432	15,574	180.0	10,365.0	684.0	25,951.0	756	1401	4	208
	Std. Dev.	186.9	20,078.8	247.6	13,048.1	379.9	5202.8	333.4	26,860.3	758.9	7419.3	1.8	257.3
	Skewness	0.54	0.47	0.56	0.99	0.30	0.71	2.60	2.08	0.03	0.12	2.16	0.86
	Kurtosis	2.33	2.67	4.11	4.03	1.82	3.23	13.19	7.49	1.96	3.05	8.16	3.62
	Jarque–Bera	5.4 *	3.3	8.4 **	16.5 ***	5.7 **	6.9 **	430.8 ***	123.1 ***	3.6	0.2	149.7 ***	11.0 ***
	Obs.	79	79	79	79	79	79	79	79	79	79	79	79
4th	Mean	855	98,663.6	1488.9	43,845.3	1018.2	26,736.4	955.8	54,780.2	1224.6	19,086.3	6.8	1513.4
	Median	828	95,145	1404	39,238	1026.0	24,583.0	900.0	51,241.0	1080	18,534	6.1	715
	Maximum	1368	157,686	2520	121,453	1341.0	57,390.0	2646.0	112,927.0	2170.2	42,992	12.5	5908
	Minimum	396	51,458	432	14,103	648.0	12,225.0	252.0	7573.0	504	2870	4.2	14
	Std. Dev.	249.2	20,000.9	463.8	19,703.3	144.6	9783.2	403.3	24,005.3	411.3	8727.1	1.7	1700.6
	Skewness	0.43	0.41	0.4	1.23	-0.32	0.85	1.29	0.39	0.46	0.65	0.91	1.15
	Kurtosis	2.68	3.04	2.54	5.21	2.58	3.24	5.78	2.36	2.26	3.28	3.58	3.01
	Jarque–Bera	3.4	2.7	3.4	43.6 ***	2.3	11.7 ***	57.0 ***	4.1	5.6 *	7.1 **	14.7 ***	21.1 ***
	Obs.	95	95	95	95	95	95	95	95	95	95	95	95

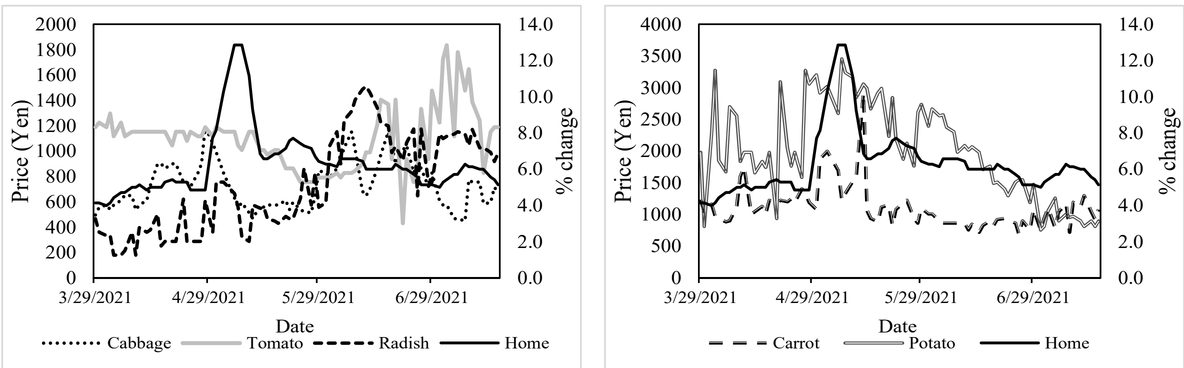
Note: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively. CP, TP, RP, CRP, and PP are the unit per price of cabbage, tomato, radish, carrot, and potato, respectively. CV, TV, RV, CRV, and PV are the total volumes traded for these five products in kilograms.



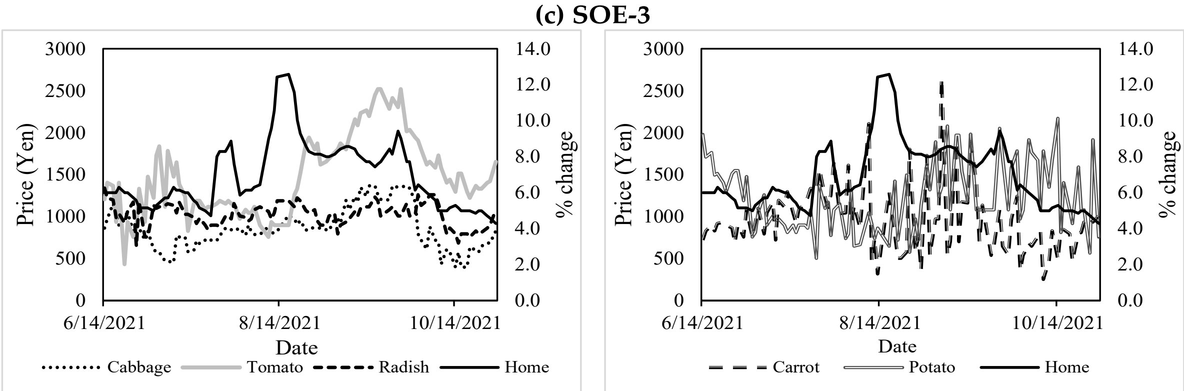
(a) SOE-1



(b) SOE-2



(c) SOE-3



(d) SOE-4

Figure 1. (**a**–**d**). Variations in cabbage, tomato, radish, carrot, and potato prices with changes in staying-at-home during the four SOE periods.

It is apparent from Figure 1 that in all SOEs, prices show very strong up-and-down trends. However, in the case of cabbage, radish, and carrot prices, SOE-1 was much more volatile compared to other SOEs. Moreover, tomato prices have a sharp decreasing trend in SOE-2 and SOE-3 but a slightly increasing trend after July 2021. It is also visible that in all SOEs, residents' staying at home was an increasing trend and then decreased significantly during the study periods.

3.2. Linear ARDL Bounds Test for Cointegration

To test for cointegration relationships among the test variables, we conducted the ARDL bound test [25]. The results shown in Table 6 demonstrate that the F-statistics is larger than the upper bounds at the 5% significance level for all vegetables except potatoes in the first SOE period. Thus, the results indicate that all vegetable models besides potatoes were cointegrated in the first SOE period.

Table 6. Bounds F-test for cointegration.

SOE	Model	F-Stat.	SOE	Model	F-Stat.
1st	Cabbage	5.012 **	3rd	Cabbage	4.110 **
	Tomato	7.873 ***		Tomato	4.720 **
	Radish	5.067 **		Radish	4.027 **
	Carrot	5.155 **		Carrot	11.075 ***
	Potato	0.513		Potato	1.533
2nd	Cabbage	10.244 ***	4th	Cabbage	4.211 **
	Tomato	1.854		Tomato	4.313 **
	Radish	2.043		Radish	3.239
	Carrot	2.161		Carrot	1.718
	Potato	11.911 ***		Potato	5.660 ***

Note: ***, and ** denote significance at 1%, and 5% levels, respectively.

In the second SOE, cabbage and potato models had a cointegration relationship based on the 1% significance level. Similar to the first SOE, all vegetables besides potato had a cointegration for the third SOE. Finally, in SOE-4, cabbage, tomato, and potato models had a cointegration. Those models with statistically significant results suggest that the variables examined move together in the long run.

Next, we estimated the ARDL model to investigate if the daily changes in residents' staying at home in the Tokyo metropolitan area have a long-term impact on the daily vegetable prices at the Toyosu wholesale market. The results of the model estimations are presented in Table 7. It is apparent from Table 7 that the daily changes in the volumes traded at the Toyosu market for cabbage had a significant and negative relationship with prices in the SOE-1 and SOE-2 periods. From the third SOE model for cabbage, it is apparent that staying at home significantly and negatively affected the price. This result is likely related to the decline in the use of restaurants during the SOE, resulting in a reduction in the market price of perishable vegetables, such as cabbage.

For tomatoes, hours of stay-at-home had a negative and statistically significant effect on the price during the first and second SOEs. This is perhaps related to a decline in human mobility due to the restrictions enforced by the SOE. In the case of radishes, volumes sold and residents staying at home had negative and significant effects on market prices.

For carrots, the stay-at-home index had a negative impact during the first SOE but did not cause a statistically significant result in the second SOE. However, in the third SOE, the effect became positive, which might be related to the increasing trend of carrot prices until the stay-at-home index peaked in early May 2021, as affected the SOE measures (see Figure 1c).

For potatoes, none of the stay-at-home indices was significant at the 1% significance level during the first to third SOEs, suggesting that the SOE restrictions did not have an impact on the potato price in these periods.

Table 7. Long-term coefficients estimation.

SOE	Model	Variable	Coefficient	Std. Error	SOE	Model	Variable	Coefficient	Std. Error
1st	Cabbage	CV	−0.017 ***	0.006	3rd	Cabbage	CV	−0.005	0.004
		Home	13.757	29.518			Home	−84.296 **	37.099
		Intercept	2160.218 ***	558.716			Intercept	1682.096 ***	562.853
	Tomato	TV	−0.045 ***	0.000		Tomato	TV	−0.018 *	0.010
		Home	−33.779 ***	18.925			Home	−8.624	25.269
		Intercept	3255.134 ***	200.373			Intercept	1397.284 ***	284.123
	Radish	RV	−0.059 ***	0.016		Radish	RV	−0.086 ***	0.030
		Home	−49.566 ***	19.489			Home	−151.611 **	70.569
		Intercept	2656.195 ***	507.184			Intercept	3316.003 ***	838.832
	Carrot	CRV	0.002 *	0.001		Carrot	CRV	0.009 ***	0.001
		Home	−23.747 **	9.825			Home	41.863 ***	15.054
		Intercept	1656.536 ***	121.651			Intercept	72.237	122.383
	Potato	PV	0.009	0.090		Potato	PV	1.668	14.053
		Home	12.450	114.869			Home	925.044	6162.287
		Intercept	2303.873	2521.096			Intercept	−19,670.67	172,079.6
2nd	Cabbage	CV	−0.004 *	0.002	4th	Cabbage	CV	−0.004	0.004
		Home	−22.739	17.277			Home	161.634 ***	36.135
		Intercept	1007.155 ***	214.296			Intercept	312.410	436.952
	Tomato	TV	−0.005	0.007		Tomato	TV	−0.043 **	0.021
		Home	−58.349 ***	21.914			Home	235.752 **	117.570
		Intercept	1600.767 ***	246.093			Intercept	1626.512 **	708.625
	Radish	RV	0.010	0.010		Radish	RV	−0.002	0.004
		Home	94.652 **	48.262			Home	37.638 *	22.480
		Intercept	−96.643	341.573			Intercept	841.351 ***	176.901
	Carrot	CRV	−0.013 **	0.007		Carrot	CRV	−0.004	0.005
		Home	−1.388	69.859			Home	−55.053	90.745
		Intercept	2242.169 ***	628.082			Intercept	1563.857 ***	545.154
	Potato	PV	−0.033 ***	0.008		Potato	PV	0.017 **	0.009
		Home	48.624	43.376			Home	99.069 **	42.242
		Intercept	2361.682 ***	289.082			Intercept	384.390	257.764

Note: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

While the hours of staying-at-home had negative impacts in the first to third SOEs on all vegetables besides carrot, the results of Table 7 indicate that the stay-at-home index had a positive effect on the prices of all vegetable except carrot for the fourth SOE. This might be due to the reluctance of people to eat at restaurants even after being vaccinated, which leads to an increase in the demand for vegetables. It could also be that following vaccination, people became less likely to stay in their homes, resulting in a positive push in demand for eating out.

Overall, except for potatoes, the SOE measures affected all vegetable prices. A recent study also identified that the potato price was less influenced by lockdown measures (a price increase of 15%) during the COVID-19 pandemic compared to perishable products such as tomatoes (a price increase of 28%) [32].

Finally, Table 8 displays the results of the short-term impacts. It can be seen from the table that radish and carrot were negatively impacted by the stay-at-home index during the first SOE, and cabbage and radish were also adversely impacted by the hours of staying-at-home, based on the 5% significance level in the short-term. These results indicate that a daily increase in the hours people stayed at home decreased vegetable prices. Again, this could be related to the decline in the number of people eating at restaurants. Furthermore, based on the 5% significance level, none of the short-term impacts were positive, suggesting that the SOE measures had an adverse impact on the vegetable price in the short-term.

Table 8. Short-term and the Tokyo COVID-19 coefficients estimations.

SOE	Model	Variable	Coefficient	Std. Error	SOE	Model	Variable	Coefficient	Std. Error
1st	Cabbage	ΔCV	−0.005 ***	0.002	3rd	Cabbage	ΔCV	−0.002 **	0.001
		ΔHome	4.182	9.027			ΔHome	−18.237 **	7.269
		TC	0.921	0.594			TC	−0.003	0.045
	Tomato	ΔTV	−0.003 *	0.001		Tomato	ΔTV	−0.001	0.002
		ΔHome	32.592 *	19.536			ΔHome	−3.407	13.601
		TC	−0.835 ***	0.296			TC	0.264 ***	0.096
	Radish	ΔRV	0.0008	0.006		Radish	ΔRV	0.008 *	0.005
		ΔHome	−22.253 ***	8.320			ΔHome	−27.445 **	10.942
		TC	−0.156	0.450			TC	0.028	0.076
	Carrot	ΔCRV	0.001 **	0.001		Carrot	ΔCRV	0.004 ***	0.001
		ΔHome	−102.695 ***	42.216			ΔHome	−56.650	47.224
		TC	−1.994 ***	0.695			TC	0.490 ***	0.134
	Potato	ΔPV	0.001	0.004		Potato	ΔPV	0.006	0.008
		ΔHome	0.792	9.654			ΔHome	−10.528	38.373
		TC	−0.234	0.739			TC	0.259	0.253
2nd	Cabbage	ΔCV	−0.001	0.001	4th	Cabbage	ΔCV	0.001	0.001
		ΔHome	9.784	8.039			ΔHome	10.91	17.682
		TC	0.083 **	0.035			TC	−0.020 **	0.01
	Tomato	ΔTV	0.001	0.002		Tomato	ΔTV	−0.004 ***	0.001
		ΔHome	−24.08	12.079			ΔHome	23.314	17.243
		TC	0.028	0.047			TC	0.014	0.019
	Radish	ΔRV	0.002	0.001		Radish	ΔRV	−0.004 *	0.002
		ΔHome	16.879 *	9.861			ΔHome	13.901 *	8.374
		TC	−0.040	0.034			TC	−0.003	0.009
	Carrot	ΔCRV	0.001	0.001		Carrot	ΔCRV	0.003	0.002
		ΔHome	−0.410	20.639			ΔHome	−22.761	32.721
		TC	−0.016	0.085			TC	0.005	0.034
	Potato	ΔPV	0.008	0.005		Potato	ΔPV	0.010 **	0.004
		ΔHome	34.767	32.753			ΔHome	−31.954	53.664
		TC	−0.204	0.147			TC	−0.076 **	0.034

Note: ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

In general, our results imply that people staying longer in their homes has an adverse impact on the prices of agricultural commodities. However, in the case of the fourth SOE, the economy of Japan started to recover; industrial activities and household consumption began to increase.

As can be seen from the results, there are cases where the stay-at-home index positively impacted vegetable prices. We conjecture that this positive impact is related to the weakening of the SOE measures as people became used to the restrictions. As seen in Table 5, the average stay-at-home hours became shorter after the second SOE, and we believe that the demand for vegetables in the Tokyo Toyosu market recovered as the SOE measures loosened.

There are certain limitations to the generalization of the findings in this study. For example, the present research is only based on the human mobility index, daily COVID-19 cases number for the Tokyo metropolitan area, and the daily volume of sales at the Toyosu market for the vegetables investigated. There is a chance that other important indicators, such as seasonality and other market indicators, might influence the market prices of both perishable and less perishable commodities. Moreover, as this is an ongoing situation, all the data we have collected are secondary sources, and these data are changing constantly. Therefore, the outcomes from our analyses are only rough indicators for the four SOE periods of the Toyosu market in Japan and its impact on the market prices of perishable and less perishable vegetables. Thus, the further study of the impact of human mobility along with seasonality and other marketing indicators should be addressed.

4. Conclusions

Human mobility has been interrupted by the COVID-19 pandemic, as many countries have had to impose restriction measures, such as lockdowns and states of emergency. Such a decrease in human mobility affected the global market prices for major fresh vegetables and the Japanese market was not an exception. To investigate the effects of the SOE on the vegetable market, this study tested how the changes in the hours of staying-at-home during the periods under the effect of a SOE influenced the Tokyo wholesale vegetable markets. This study explored some interesting results by identifying the effects of staying at home on the changing market prices of major fresh vegetables (cabbage, tomato, radish, potato, and carrot).

During the initial SOEs, people were more concerned about staying at home and spent more in their homes during that SOE period. We found a more negative influence of the stay-at-home measures during the initial SOEs on vegetable prices, and the study results indicate that this was due to the reduction in human mobility related to the SOE measure. However, a less perishable vegetable, the potato, did not receive such a negative influence from the measure.

We also found that in the fourth SOE, the stay-at-home restrictions no longer influenced the price adversely but positively affected specific vegetable prices. As time passed and the number of people being vaccinated increased, the SOE measure likely lost its effect, and more people went out even when the SOE was announced.

All in all, the study revealed that when the SOE measures are effective at keeping people in their homes and lead to a reduction in human mobility, such regulations can cause adverse impacts on vegetable prices. The key findings indicate the importance of implementing a pricing policy, such as providing subsidies to farmers that are likely to lose their sales when vegetable prices decrease, as the SOE measures restrict human mobility. In addition, our study suggested that prices of perishable vegetables are more likely to be influenced by human mobility restrictions during the pandemic compared to less perishable products, suggesting that policymakers need to provide more support to mitigate the effects of the price drop for these items.

Although this was one of the first studies to reveal that the restriction of human mobility can lead to a decrease in vegetable prices, more research needs to be performed to find out the causes of such price decreases as related to the pandemic and which other market participants besides the producers, for example, retailers, might face drawbacks from the pandemic.

Author Contributions: Conceptualization, K.A., M.M.I., and A.J.; methodology, K.A.; formal analysis, K.A.; data curation, K.A., M.M.I., and A.J.; writing—original draft preparation, K.A., M.M.I., and A.J.; writing—review and editing, K.A., M.M.I., and A.J.; supervision, K.A. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: Daily market prices for cabbage, potato, radish, tomato, and carrot are available on the homepage of MCWM (2022). The data for the daily changes in the human mobility data are available at https://ourworldindata.org/COVID-google-mobility-trends (accessed on 6 February 2022). The data for the daily number of COVID-19 cases in Tokyo are available at https://stopcovid19.metro.tokyo.lg.jp (accessed on 25 February 2022).

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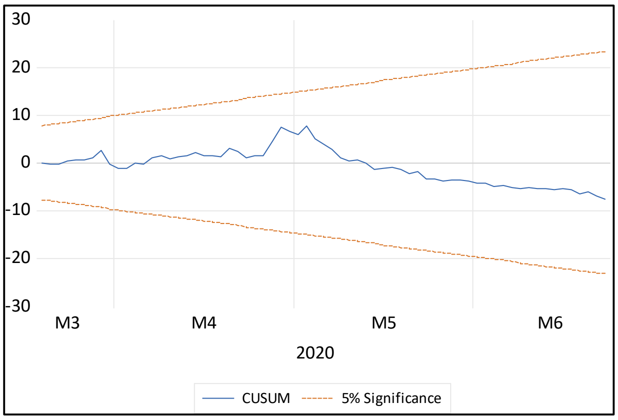
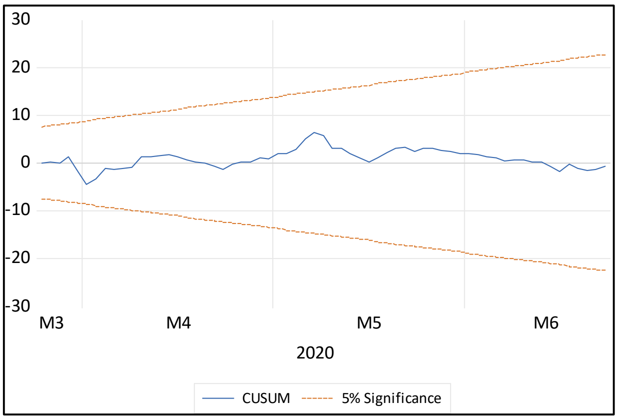
Conflicts of Interest: The authors declare no conflict of interest.

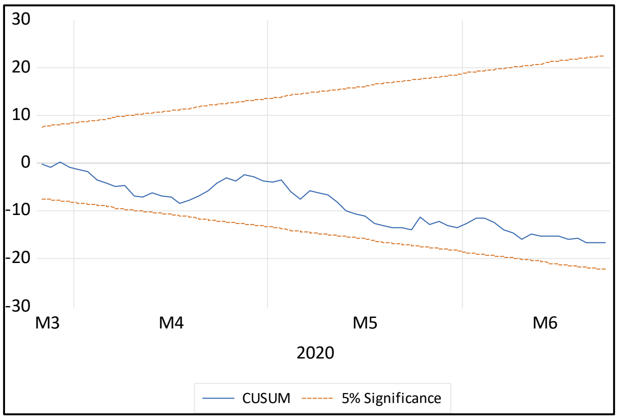
Appendix A. ARDL Cumulative Sum (CUSUM) Test for Stability



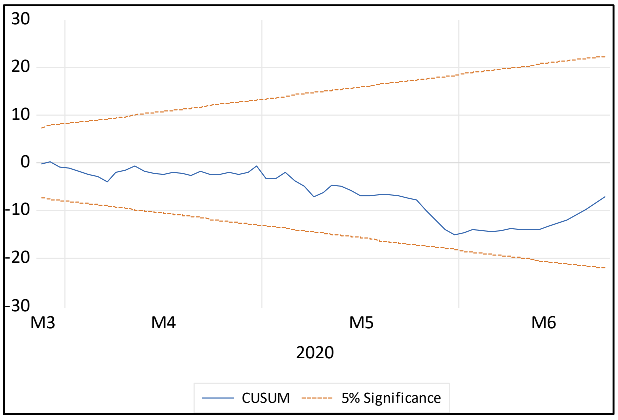
(a) Cabbage



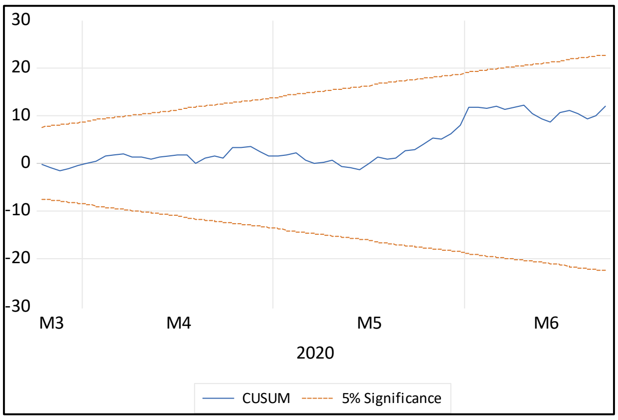
(b) Tomato



(c) Radish

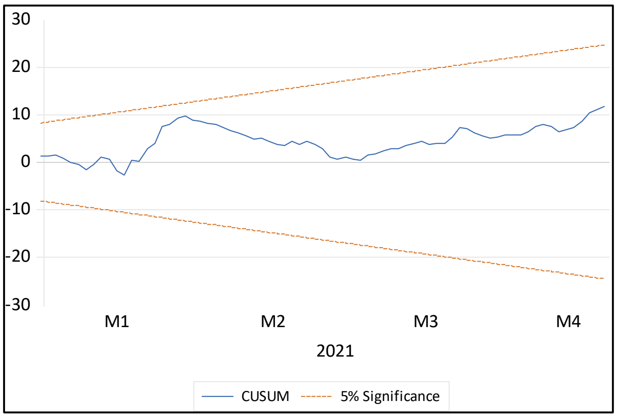


(d) Carrot

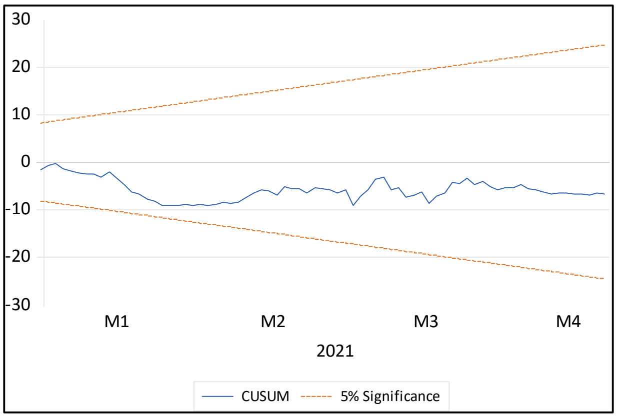


(e) Potato

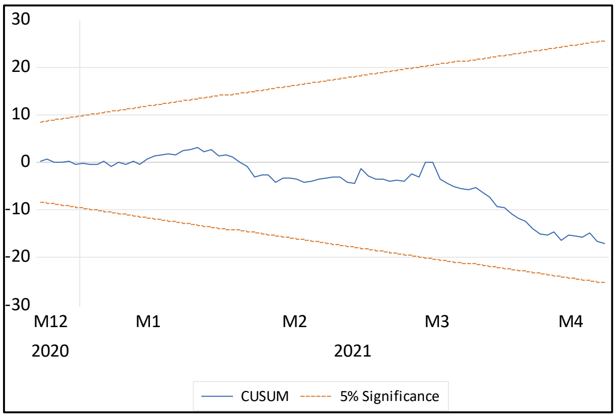
Figure A1. CUSUM tests for SOE-1.



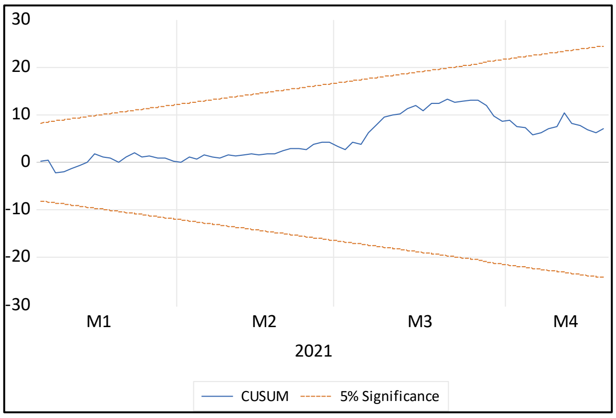
(a) Cabbage



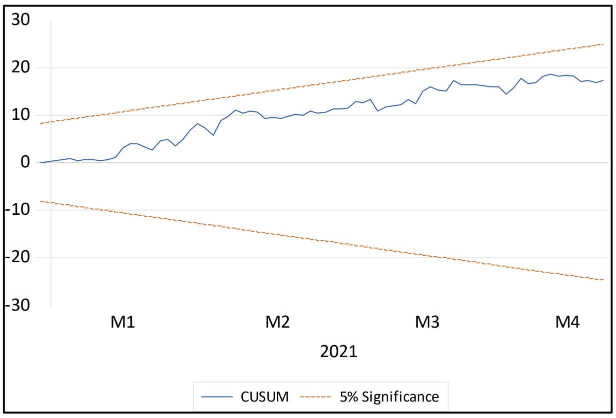
(b) Tomato



(c) Radish

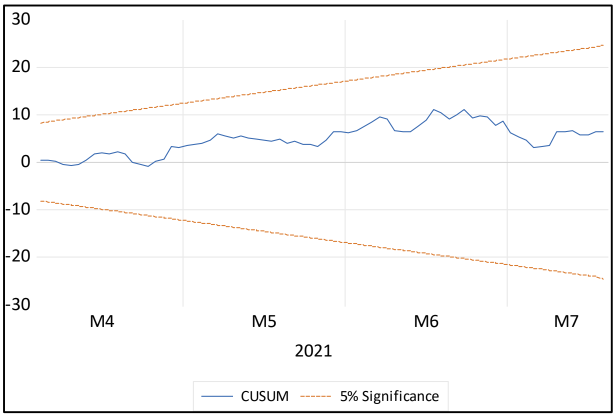


(d) Carrot

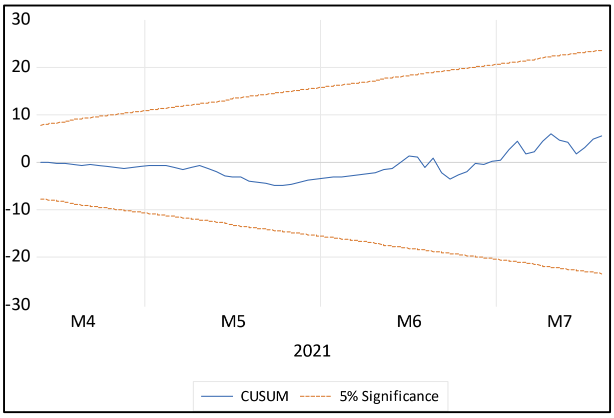


(e) Potato

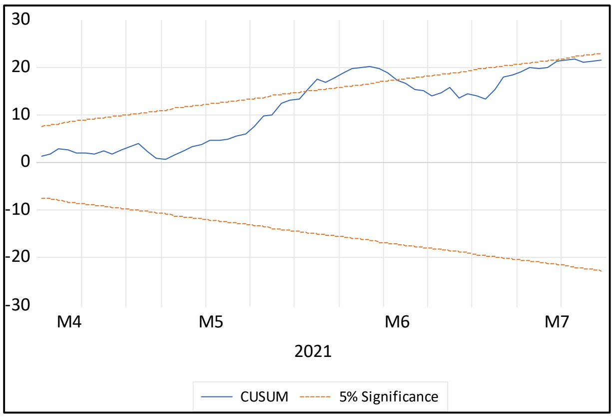
Figure A2. CUSUM tests for SOE-2.



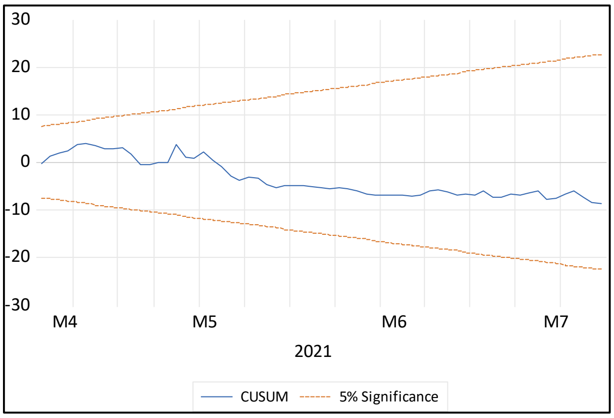
(a) Cabbage



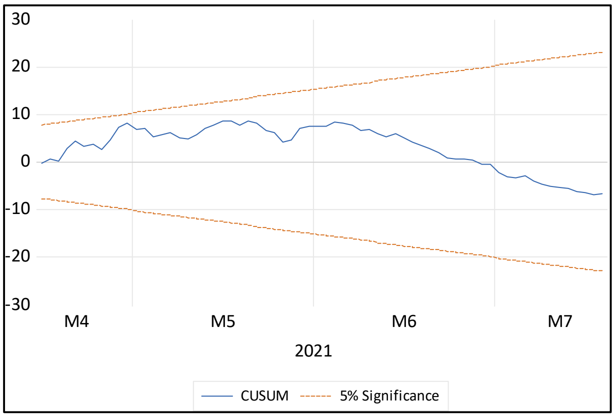
(b) Tomato



(c) Radish

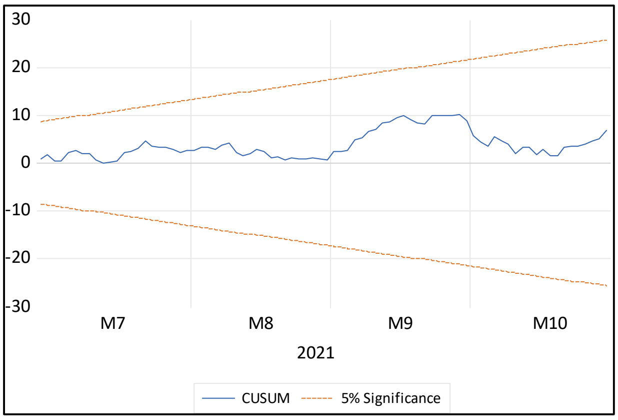


(d) Carrot

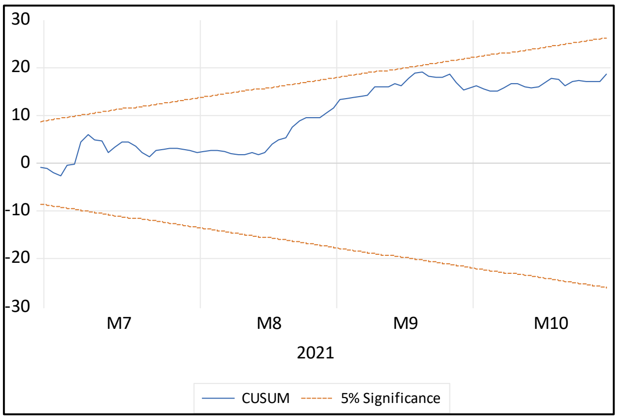


(e) Potato

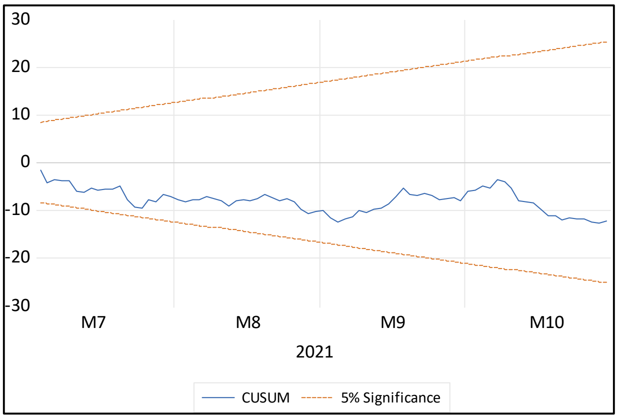
Figure A3. CUSUM tests for SOE-3.



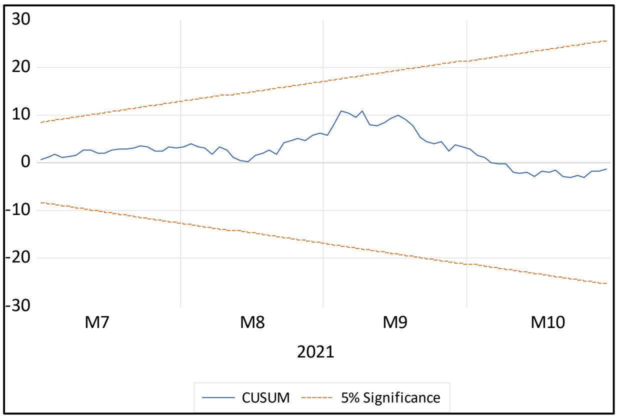
(a) Cabbage



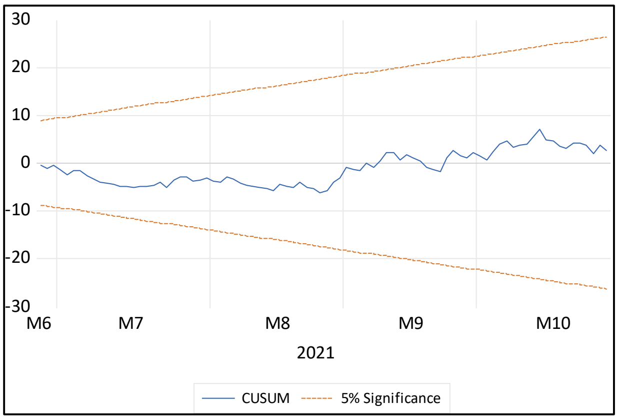
(b) Tomato



(c) Radish



(d) Carrot



(e) Potato

Figure A4. CUSUM tests for SOE-4.

References

1. Hadjidemetriou, G.M.; Sasidharan, M.; Kouyialis, G.; Parlikad, A.K. The impact of government measures and human mobility trend on COVID-19 related deaths in the UK. *Transp. Res. Interdiscip. Perspect.* **2020**, *6*, 100167. [CrossRef] [PubMed]
2. Tison, G.H.; Avram, R.; Kuhar, P.; Abreau, S.; Marcus, G.M.; Pletcher, M.J.; Olgin, J.E. Worldwide effect of COVID-19 on physical activity: A descriptive study. *Ann. Intern. Med.* **2020**, *173*, 767–770. [CrossRef] [PubMed]
3. Alam, G.M.M.; Khatun, M.N. Impact of COVID-19 on vegetable supply chain and food security: Empirical evidence from Bangladesh. *PLoS ONE* **2021**, *16*, e0248120. [CrossRef] [PubMed]
4. Richards, T.J.; Rickard, B. COVID-19 impact on fruit and vegetable markets. *Can. J. Agric. Econ.* **2020**, *68*, 189–194. [CrossRef]

5. Singh, S.; Kumar, R.; Panchal, R.; Tiwari, M.K. Impact of COVID-19 on logistics systems and disruptions in food supply chain. *Int. J. Prod. Res.* **2021**, *59*, 1993–2008. [CrossRef]
6. Deaton, B.J.; Deaton, B.J. Food security and Canada's agricultural system challenged by COVID-19. *Can. J. Agric. Econ.* **2020**, *68*, 143–149. [CrossRef]
7. Reddy, V.R.; Singh, S.K.; Anbumozhi, S. *Food Supply Chain Disruption due to National Disasters: Entities, Risks, and Strategies for Resilience*; ERIA Discussion Paper Series; Economic Research Institute for ASEAN and Asia: Jakarta, Indonesia, 2016.
8. Chari, F.; Muzinda, O.; Novukela, C.; Ngcamu, B.S. Pandemic outbreaks and food supply chains in developing countries: A case of COVID-19 in Zimbabwe. *Cogent Bus. Manag.* **2022**, *9*, 2026188. [CrossRef]
9. USDA, COVID-19 Impacts on Food Distribution in Japan-Update II, 2020. Available online: https://apps.fas.usda.gov/newgainapi/api/Report/DownloadReportByFileName?fileName=COVID-19%20Impacts%20on%20Food%20Distribution%20in%20Japan%20-%20Update%20II_Tokyo%20ATO_Japan_05-26-2020 (accessed on 23 June 2021).
10. IMF. International Monetary Fund. World Economic Outlook Update, June 2020. Available online: https://www.imf.org/en/Publications/WEO/Issues/2020/06/24/WEOUpdateJune2020 (accessed on 23 June 2021).
11. Lichten, J.; Kondo, C. Resilient Japanese local food systems thrive during COVID-19: Ten groups, ten outcomes. This article is a part of The Special Issue: Vulnerable Populations Under COVID-19 in Japan. *Aisa-Pac. J.* **2020**, *18*. Available online: https://apjjf.org/2020/18/Kondo-Lichten.html (accessed on 22 February 2022).
12. Islam, M.M.; Jannat, A.; Al Rafi, D.A.; Aruga, K. Potential economic impacts of the COVID-19 pandemic on South Asian economies: A review. *World* **2020**, *1*, 283–299. [CrossRef]
13. Nickle, A. Retail Produce Sales Rising Amid Coronavirus Concerns. The Packer. 2020. Available online: https://www.thepacker.com/article/retail-produce-sales-rising-amid-coronavirus-concerns? (accessed on 25 April 2021).
14. Aruga, K.; Islam, M.M.; Jannat, A. Does Staying at Home during the COVID-19 Pandemic Help Reduce CO_2 Emissions? *Sustainability* **2021**, *13*, 8534. [CrossRef]
15. Jena, P.R.; Kalli, R.; Tanti, P.C. Impact of COVID-19 on Agricultural System and Food Prices: The Case of India. In *Rural Health*; IntechOpen: London, UK, 2021. [CrossRef]
16. Chen, J.; Yang, C.-C. How COVID-19 Affects Agricultural Food Sales: Based on the Perspective of China's Agricultural Listed Companies' Financial Statements. *Agriculture* **2021**, *11*, 1285. [CrossRef]
17. Reardon, T.; Bellemare, M.F.; Zilberman, D. How COVID-19 May Disrupt Food Supply Chains in Developing Countries. IFPRI Book Chapters: 2020, 78–80. Available online: https://www.ifpri.org/blog/how-covid-19-may-disrupt-food-supply-chains-developing-countries (accessed on 7 March 2022).
18. Akter, S. The impact of COVID-19 related 'stay-at-home' restrictions on food prices in Europe: Findings from a preliminary analysis. *Food Secur.* **2020**, *12*, 719–725. [CrossRef] [PubMed]
19. World Population Review. Japan Population, 2022 (Live). Available online: https://worldpopulationreview.com/countries/japan-population (accessed on 22 February 2022).
20. Statista. Most Commonly Eaten Fruits and Vegetables in Japan as of November. 2020. Available online: https://www.statista.com/statistics/1229250/japan-most-eaten-fruit/ (accessed on 23 June 2021).
21. Kohls, R.L. *Marketing of Agricultural Products*, 9th ed.; Prentice Hall: Upper Saddle River, NJ, USA, 2002.
22. Metropolitan Central Wholesale Market (MCWM). Metropolitan Central Wholesale Market Daily Report. 2022. Available online: https://www.shijou-nippo.metro.tokyo.lg.jp/index.html (accessed on 9 February 2022).
23. Google LLC. Google COVID-19 Community Mobility Reports. Available online: https://www.google.com/covid19/mobility/ (accessed on 6 February 2021).
24. Phillips, P.C.; Perron, P. Testing for a unit root in time series regression. *Biometrika* **1988**, *75*, 335–346. [CrossRef]
25. Dickey, D.A.; Fuller, W.A. Distribution of the estimators for autoregressive time series with a unit root. *J Am. Stat. Assoc.* **1979**, *74*, 427–431.
26. Kwiatkowski, D.; Phillips, P.C.; Schmidt, P.; Shin, Y. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *J. Econom.* **1992**, *54*, 159–178. [CrossRef]
27. Pesaran, M.H.; Shin, Y.; Smith, R.J. Bounds testing approaches to the analysis of level relationships. *J. Appl. Econ.* **2001**, *16*, 289–326. [CrossRef]
28. Nyga-Łukaszewska, H.; Aruga, K. Energy prices, and COVID-immunity: The case of crude oil and natural gas prices in the US and Japan. *Energies* **2020**, *13*, 6300. [CrossRef]
29. Breusch, T.S. Testing for Autocorrelation in Dynamic Linear Models. *Aust. Econ. Pap.* **1978**, *17*, 334–355. [CrossRef]
30. Godfrey, L.G. Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables. *Econometrica* **1978**, *46*, 1293. [CrossRef]
31. Breusch, T.S.; Pagan, A.R. A simple test for heteroscedasticity and random coefficient variation. *Econometrica* **1979**, *47*, 1287. [CrossRef]
32. Sudha, N.; Shree, S. Urban Food Markets and the Lockdown in India. 2020. Available online: https://doi.org/10.2139/ssrn.3599102 (accessed on 23 June 2021).