



Article

Changes in Human Mobility under the COVID-19 Pandemic and the Tokyo Fuel Market

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Abstract: The study identifies the impact of the changes in human mobility due to the announcement of the state of emergency to cope with the COVID-19 pandemic on the Tokyo gasoline, diesel, and kerosene markets. Indices reflecting the movements in the visits to transit stations and workplaces were used to capture the changes in human mobility from February 2020 to February 2021. The linear and nonlinear ARDL (NARDL) models were applied to investigate the relationship between the changes in human mobility indices and fuel prices. Although only the kerosene price received an impact from the human mobility changes in the linear ARDL model, the NARDL model revealed that when human mobility was increasing, the fuel price was affected positively and the negative shocks in the mobility had an adverse influence on the fuel price. The results of the study imply the importance of providing subsidies when a state of emergency reduces fuel demands due to the decline in human mobility and negatively affects the fuel retail industry.

Keywords: human mobility; gasoline; diesel; kerosene; ARDL; NARDL



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1. Introduction

It is reported that the number of gas stations going out of business from January to October 2020 in Japan exceeded the annual total bankruptcies of gas stations in 2019 (Tokyo Shoko Research 2021), suggesting that the COVID-19 pandemic is casting dark clouds over the Japanese gasoline retail industry. On 8 January 2021, the second state of emergency was enforced in Tokyo, which is expected to further dampen the gasoline demand (Kumagai et al. 2021).

Although the state of emergency rules in Japan has not been a severe stay-at-home order like the lockdown regulations with penalties in the European countries, the Japanese government asked people to refrain from nonessential and nonurgent outings, institutions and companies to increase the number of employees working remotely, and restaurants and bars to close earlier than their usual business hours.

Figure 1 illustrates the changes in human mobility in Japan after the COVID-19 outbreak became apparent in early 2020. The figure also shows the changes in the number of visits to transit stations and workplaces during the first and second states of emergency. It is discernible from the figure that although the Japanese state of emergency rule was not as strict compared to other countries, the level of human mobility somewhat declined after the rule was enforced. Hence, I expect that this impact on human mobility due to the state of emergency lowered the demand for fuels such as gasoline, diesel, and kerosene.

However, up until now, no studies have tested whether changes in human mobility during the COVID-19 pandemic had influences on the fuel market. Thus, the objective of the study is to investigate how the changes in human mobility during the pandemic due to the spread of the coronavirus and the announcement of the state of emergency have impacted the fuel markets. By identifying the impact of the human mobility changes on the fuel price, the study expects to provide important information for the government considering a subsidy policy for the fuel industry that might face serious damages if the

plunge in automobile usage due to stay-at-home orders causes the fuel price to plummet. Besides, the results of the study can offer a valuable reference for understanding how the fuel market will be affected by changes in human mobility not only in the time of the pandemic but also in other situations.

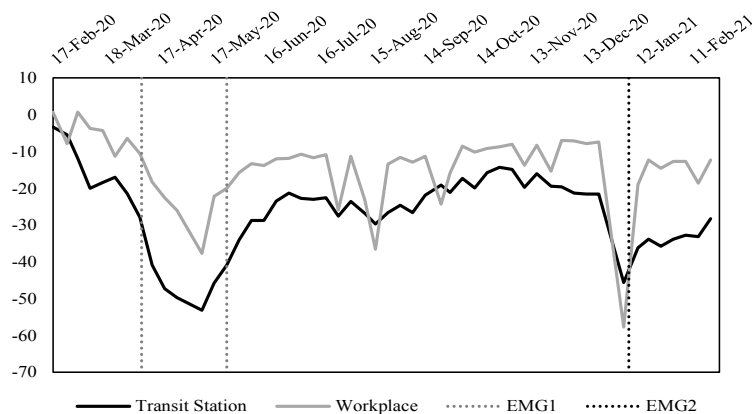


Figure 1. Indices for the number of visits to transit stations and workplaces between 17 February 2020 and 22 February 2021 in Japan. EMG1 indicates the starting (7 April 2020) and ending (25 May 2020) periods of the first state of emergency and EMG2 denotes the starting period (8 January 2021) of the second state of emergency enforced in Tokyo.

To accomplish the research objective, the case of Tokyo, Japan, was selected for investigation. The Tokyo fuel market was chosen as a case study because as of March 2021, Tokyo had the largest accumulative number of COVID-19 cases among all Japanese cities, and thus, it is the most suitable city for investigation of the impact of the pandemic on the fuel market for Japan. The study uses the number of visits to transit stations and workplaces for indices representing the changes in human mobility in Japan during the pandemic. The types of fuel prices investigated in the study are the premium and regular gasoline, diesel, and kerosene prices because these fuels are all commonly sold fuels at local gas stations in Tokyo.

Numerous studies have examined the effects of an external shock on oil prices (Sadorsky 1999; Hamilton 2003; Farzanegan and Markwardt 2009; Wen et al. 2019), but most of these studies focus on how changes in the oil market due to the shock affected the economy and stock markets. The current study is related to studies investigating how events like the 2008 financial crisis have influenced the oil market (Aruga 2015; Joo et al. 2020). Recently, researchers have begun to conduct studies to understand how the ongoing COVID-19 pandemic is causing impacts on the energy markets (Alhajeri et al. 2020; Aruga et al. 2020; Nyga-Łukaszewska and Aruga 2020), but it is still unknown how the changes in human mobility during the COVID-19 incident is affecting the energy markets.

In studies investigating the effects of the COVID-19 pandemic on human mobility changes, Hadjidemetriou et al. (2020) identified that lockdown measures conducted by the UK government in March 2020 reduced human mobility dramatically. Archer et al. (2020) found that COVID-19 decreased the use of passenger vehicles fueled by gasoline, leading to a reduction in vehicle NO₂ emissions in the US. Eisenmann et al. (2021) conducted a survey in Germany to understand the changes in people's travel behavior during the COVID-19 pandemic and determined that public transport lost ground while private cars gained importance. Thus, it is probable that changes in human mobility during the COVID-19 period will also impact fuel prices, but up until now, no studies have investigated this issue.

Among the previous studies, that of Nyga-Łukaszewska and Aruga (2020) is the most relevant. It analyzed the impact of the number of COVID-19 cases on the crude oil and natural gas markets, finding that while the crude oil market was affected negatively by the number of COVID-19 cases, the natural gas market was impacted positively. The present study is different from this study as it examines how the human mobility changes caused

impacts on gasoline, diesel, and kerosene prices. Compared to the number of COVID-19 cases, the data for changes in human mobility during the pandemic are more directly connected to energy consumption because when more people are staying at home during the state of the emergency, the use of automobile fuels such as gasoline and diesel will drop. Besides, as the study uses fuel prices like gasoline and diesel prices instead of the crude oil price, the study is expected to reveal the influence of the COVID-19 pandemic on energy prices more accurately by examining the effects of human mobility changes on fuel prices. Furthermore, this study is novel because it applies the recently developed nonlinear auto-regressive distributed lag (NARDL) model while the previous study only applied the ARDL model.

In the next section, the methods used in the study are explained. The third section describes the results of the analyses and discusses the implications of the results. In the final section, the conclusions are drawn.

2. Methods

The study introduces the following equation to investigate the impact of the changes in human mobility on fuel prices:

$$price_t = C + \beta_1 transit + \beta_2 work + \beta_3 EMG_1 + \beta_4 EMG_2 \quad (1)$$

This equation is based on the model developed by [Nyga-Lukaszewska and Aruga \(2020\)](#) analyzing the effects of the COVID-19 pandemic on energy prices. In this equation, the changes in human mobility are used as a variable to examine the effects of the COVID-19 pandemic on energy prices, while [Nyga-Lukaszewska and Aruga \(2020\)](#) used the number of COVID-19 cases for this purpose.

In Equation (1), *price* is either the average weekly price of 1 kiloliter of premium gasoline, regular gasoline, diesel, and kerosene sold in the Tokyo area denoted in Japanese Yen (JPY). The Tokyo fuel price data were obtained from the homepage of the Agency for Natural Resources and Energy of the Ministry of Economy, Trade and Industry, Japan. Figure 2 delineates the plots of the fuel prices used in the study. It is observable from the figure that the fuel prices had a downward trend at the beginning of the series until near the period when the first state of emergency ended. They then stayed relatively flat but started to increase after mid-November 2020.

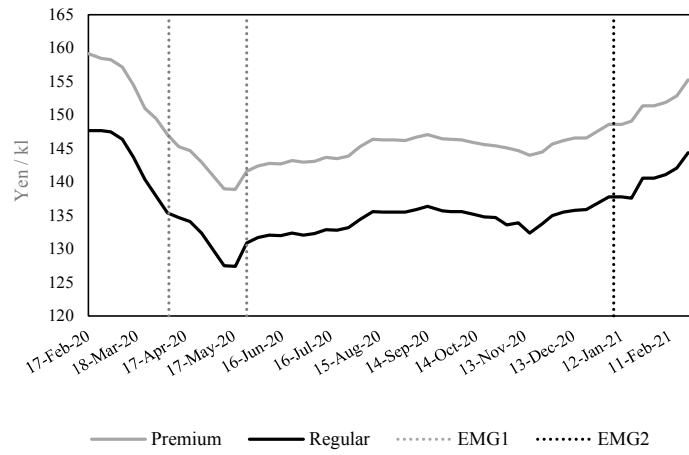
Transit and *work* in Equation (1) are the changes in the visitors to transit stations and workplaces in Japan relative to a baseline day, where the baseline day is defined as the median value between 3 January and 6 February 2020. The plots of these data are presented in Figure 1. These human mobility data were collected from the homepage of Our World in Data, which is based on the Google Global Mobility Report for Japan.

The fuel price and human mobility data used in the study are the weekly data between 17 February 2020 and 22 February 2021.

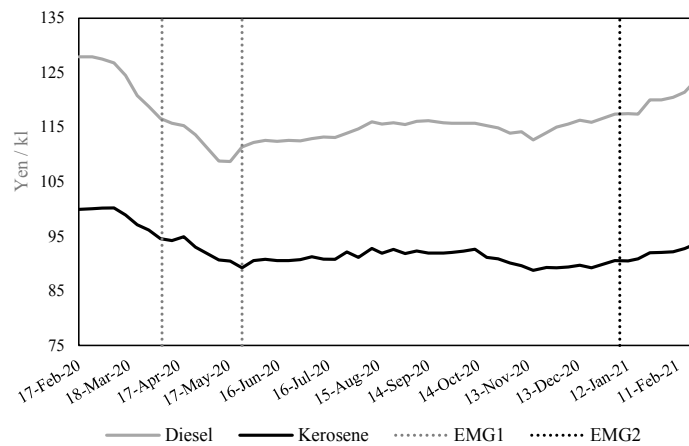
Besides the human mobility variables, I included variables to consider the effects of the state of emergency on the fuel prices in Equation (1). EMG_1 and EMG_2 represent these variables. These variables are dummy variables taking 1 when the period belongs to the time when the first and second states of emergency were enforced in Tokyo. As Tokyo was under the first state of emergency from 7 April to 25 May 2020, EMG_1 is coded as 1 when the data contained this period. The second state of emergency started on 8 January 2021 and continued until the final data period obtained in this study, so EMG_2 is coded as 1 for periods later than 8 January 2021.

As the aim of the study was to identify both the short-run and long-run impacts of the human mobility changes on the fuel prices, the application of the auto-regressive distributed lag (ARDL) model proposed by [Pesaran et al. \(2001\)](#) was deemed appropriate. The ARDL is useful for testing a cointegration relationship even when all the test variables are not integrated of the same order: the variables can be either I(1) or I(0). Furthermore, the ARDL model does not lose its power when omitted variables and auto-correlation issues are sustained in the data and is useful for analyzing data with small sample sizes.

The study also applies the nonlinear ARDL (NARDL) model developed by Shin et al. (2014) to capture the asymmetric adjustment patterns regarding the positive and negative shocks of human mobility on fuel prices.



(a)



(b)

Figure 2. Fuel prices between 17 February 2020 and 22 February 2021. (a) Premium and regular gasoline; (b) diesel and kerosene. EMG1 indicates the starting and ending periods of the first state of emergency and EMG2 denotes the starting period of the second state of emergency.

First, to confirm the orders of integration of the variables investigated in the study, the Zivot and Andrews (1992) unit root tests were conducted on the sample. ZA is known to have an advantage in testing unit roots when the data contain a structural break. The test conducts the stationarity test by internally determining the single structural break in the series. Table 1 depicts the results of this test. The table indicates that except *workplace*, all the variables are integrated of order one (I(1)). *Workplace* is also I(0), suggesting that the variables used in this study satisfy the requirements for applying the ARDL model.

Table 1. Zivot–Andrews unit root tests.

| | Levels | | First Differences | | |
|-----------|-----------------|----------------|-------------------|-----|---------------|
| | <i>t</i> -Stat. | Breakpoint | <i>t</i> -Stat. | | Breakpoint |
| Premium | −3.46 | 21-December-20 | −5.25 | ** | 10-August-20 |
| Regular | −3.84 | 16-November-20 | −5.23 | ** | 1-January-20 |
| Diesel | −3.47 | 16-November-20 | −5.25 | ** | 10-August-20 |
| Kerosene | −2.44 | 4-April-20 | −5.14 | ** | 12-October-20 |
| Transit | −4.79 | 27-April-20 | −6.70 | *** | 20-April-20 |
| Workplace | −9.04 | 27-April-20 | −8.02 | *** | 18-May-20 |

Note: The test allowed for a structural break in both intercept and trend. *** and ** denote significance at the 1% and 5% levels, respectively.

Second, the ARDL estimation was performed with the following unrestricted error correction model:

$$\Delta price_t = C + \beta_1 price_{t-1} + \beta_2 transit_{t-1} + \beta_3 work_{t-1} + \sum_{i=1}^p \beta_{4i} \Delta price_{t-i} + \sum_{i=0}^q \beta_{5i} \Delta transit_{t-i} + \sum_{i=0}^r \beta_{6i} \Delta work_{t-i} + \beta_7 EMG_1 + \beta_8 EMG_2 + \varepsilon_t \tag{2}$$

Finally, based on Equation (2), the NARDL model was applied to estimate the relationship presented in Equation (1). For applying the NARDL, *transit* and *work* were decomposed into positive and negative cumulative sums. Let *visit_t* be either number of visits to transit stations or workplaces. Then, *visit_t* can be decomposed into positive and negative partial sums:

$$visit_t^+ = \sum_{i=1}^t \Delta visit_i^+ = \sum_{i=1}^t \max(\Delta visit_i, 0), \quad visit_t^- = \sum_{i=1}^t \Delta visit_i^- = \sum_{i=1}^t \min(\Delta visit_i, 0). \tag{3}$$

Based on the decomposition in Equation (3), the *transit* and *work* in Equation (2) are replaced by the positive and negative partial sums of these variables. Using these variables, the NARDL unrestricted error correction model was estimated under the following equation:

$$\Delta price_t = C + \beta_1 price_{t-1} + \beta_2 transit_{t-1}^+ + \beta_3 transit_{t-1}^- + \beta_4 work_{t-1}^+ + \beta_5 work_{t-1}^- + \sum_{i=1}^p \beta_{6i} \Delta price_{t-i} + \sum_{i=0}^q (\tau_i^+ \Delta transit_{t-i}^+ + \tau_i^- \Delta transit_{t-i}^-) + \sum_{i=0}^r (\varphi_i^+ \Delta work_{t-i}^+ + \varphi_i^- \Delta work_{t-i}^-) + \beta_7 EMG_1 + \beta_8 EMG_2 + \varepsilon_t \tag{4}$$

In both the ARDL and NARDL models, the optimal lag orders of the dependent and explanatory variables included in the models are identified by the Akaike information criterion (AIC).

To test if the models contain serial correlation and heteroskedasticity issues, the Breusch–Godfrey test for autocorrelation (Breusch 1978; Godfrey 1978) and the Breusch and Pagan (1979) test for heteroskedasticity were performed. The cumulative sum (CUSUM) and the cumulative sum of squares (CUSUMSQ) tests were also conducted to examine the stability of the parameters estimated by the ARDL and NARDL models.

3. Results and Discussions

The error correction model requires the fuel price and human mobility variables to be cointegrated, so the bounds F-test was conducted on the ARDL model. Table 2 shows the results of this test. The results indicate that all four fuel price models have a cointegration relationship. However, the long-run estimation results in Table 3 implies that these cointegration relationships are not driven by the human mobility variables.

Table 2. Linear ARDL bounds test for cointegration.

| Fuel Prices | | F-Stat. | |
|--------------------|------|---------|------|
| Premium | 6.63 | | *** |
| Regular | 5.23 | | *** |
| Diesel | 5.34 | | *** |
| Kerosene | 4.06 | | ** |
| Significance level | | I(0) | I(1) |
| 1% level | | 4.13 | 5.00 |
| 5% level | | 3.10 | 3.87 |
| 10% level | | 2.63 | 3.35 |

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

Table 3. Linear ARDL long-run estimation.

| Variables | Premium | | Regular | | Diesel | | Kerosene | | | | | |
|-----------|---------|---------|---------|---------|--------|---------|----------|---------|-------|-------|-----|-------|
| | Coef. | t-Stat. | Coef. | t-Stat. | Coef. | t-Stat. | Coef. | t-Stat. | | | | |
| Constant | 146.13 | *** | 40.73 | 136.23 | *** | 33.99 | 118.94 | *** | 28.99 | 82.87 | *** | 11.98 |
| Transit | −0.01 | | −0.05 | 0.04 | | 0.20 | 0.05 | | 0.27 | −0.54 | | −1.64 |
| Work | 0.05 | | 0.64 | 0.05 | | 0.68 | 0.20 | * | 1.95 | 0.30 | * | 1.91 |

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

The short-run effects of the changes in human mobility on fuel prices were also examined. According to Table 4, although the short-run influences caused by the changes in human mobility indices did not become apparent in the gasoline and diesel models, the result of the kerosene model suggests that an increase in the index for transit station visits affected the kerosene price negatively. As kerosene is mostly used for home heating devices in Japan, this result might indicate that when more people were going out of their homes, the total use of heating devices declined, which led to a decrease in the kerosene demand. Hence, it is probable that an increase in transit station visits adversely affected the kerosene price due to the decreased kerosene demand. The coefficients of the states of emergency suggest that during the second state of emergency, the premium and regular gasoline and diesel prices had an upward trend while the first state of emergency coefficient only affected the kerosene price with a negative impact.

Table 4. Linear ARDL model estimation.

| ΔPremium | | | | ΔRegular | | | | ΔDiesel | | | | ΔKerosene | | | |
|----------------------|-------|--------|-------|----------------------|-------|--------|-------|-------------------|-------|--------|-------|-------------------|-------|--------|-------|
| Variables | Coef. | t-Stat | | Variables | Coef. | t-Stat | | Variables | Coef. | t-Stat | | Variables | Coef. | t-Stat | |
| Constant | 30.34 | *** | 4.80 | Constant | 30.50 | *** | 4.31 | Constant | 25.76 | *** | 4.40 | Constant | 9.17 | ** | 2.38 |
| Premium(-1) | −0.21 | *** | −4.96 | Regular(-1) | −0.22 | *** | −4.45 | Diesel(-1) | −0.22 | *** | −4.52 | Kerosene(-1) | −0.11 | *** | −2.76 |
| Transit ^a | 0.00 | | −0.04 | Transit ^a | 0.01 | | 0.17 | Transit(-1) | 0.01 | | 0.28 | Transit(-1) | −0.06 | ** | −2.28 |
| Work ^a | 0.01 | | 0.51 | Work ^a | 0.01 | | 0.45 | Work ^a | 0.04 | | 1.56 | Work ^a | 0.03 | * | 1.86 |
| ΔPremium(-1) | 0.28 | ** | 2.06 | ΔRegular(-1) | 0.22 | | 1.47 | ΔDiesel(-1) | 0.27 | * | 1.86 | ΔKerosene(-1) | −0.17 | | −1.29 |
| ΔPremium(-2) | −0.33 | ** | −2.05 | ΔRegular(-2) | −0.22 | | −1.36 | ΔTransit | −0.06 | | −1.09 | ΔTransit | −0.12 | *** | −3.05 |
| EMG1 | −1.67 | | −1.67 | EMG1 | −1.28 | | −0.99 | EMG1 | −0.42 | | −0.45 | EMG1 | −2.01 | *** | −3.39 |
| EMG2 | 2.07 | *** | 3.57 | EMG2 | 2.22 | *** | 3.10 | EMG2 | 1.97 | *** | 3.07 | EMG2 | 0.07 | | 0.18 |

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. ^a Indicates the variable is interpreted as $Z = Z(-1) + \Delta Z$.

Similarly, the NARDL model was estimated. First, the cointegration test was conducted by the bounds F-test. As seen in Table 5, the gasoline and diesel price models contained a cointegration relationship based on the 5% significance level. The kerosene model also had this relationship, although the null hypothesis of no cointegration was rejected only at the 10% level.

Table 5. NARDL bounds test for cointegration.

| Fuel Prices | | F-Stat. | |
|--------------------|------|---------|------|
| Premium | 7.30 | | *** |
| Regular | 3.60 | | ** |
| Diesel | 3.64 | | ** |
| Kerosene | 3.22 | | * |
| Significance level | I(0) | | I(1) |
| 1% level | 3.29 | | 4.37 |
| 5% level | 2.56 | | 3.49 |
| 10% level | 2.2 | | 3.09 |

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

Then, the long-run coefficients of the NARDL model were estimated, and the result of this estimation is depicted in Table 6. It is evident from the table that the negative shock in the number of visits to transit stations had a positive impact on premium and regular gasoline and diesel prices. This might imply that when the number of transit station visits was increasing, people tended to shift their commuting methods from public transportation to automobiles, leading to an increase in fuel demand in the long run. On the other hand, the negative shock in the workplace visits negatively impacted gasoline and diesel prices. This result is perhaps because the state of emergency forced people to stay longer at their homes, leading the fuel demand to drop in the long run.

Table 6. NARDL long-run estimation.

| Variables | Premium | | Regular | | Diesel | | Kerosene | | | | |
|-----------|---------|---------|---------|---------|--------|---------|----------|---------|-------|-------|-------|
| | Coef. | t-Stat. | Coef. | t-Stat. | Coef. | t-Stat. | Coef. | t-Stat. | | | |
| Constant | 171.34 | *** | 119.60 | *** | 26.98 | *** | 28.66 | *** | 87.01 | *** | 7.24 |
| Transit+ | −0.01 | | −0.15 | ** | −2.12 | * | −1.97 | * | −0.42 | | −1.62 |
| Transit- | 0.91 | *** | 14.96 | *** | 4.12 | *** | 0.71 | *** | 4.52 | −0.45 | −0.80 |
| Work+ | −0.14 | * | −1.93 | * | 1.86 | * | 0.11 | * | 1.75 | 0.30 | 1.65 |
| Work- | −0.53 | *** | −5.73 | ** | −2.68 | ** | −0.29 | *** | −2.93 | 0.33 | 0.99 |

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

Finally, the results of short-run effects of the human mobility indices on the fuel prices are presented in Table 7. The short-run coefficient of the positive changes in the visits to transit stations index (Δ Transit+) for the premium gasoline indicates that when the number of transit station visits is increasing, the premium gasoline price is increasing. In contrast, the short-run coefficient of the negative changes in the transit station visits (Δ Transit-) suggests that the premium gasoline price has a declining trend when the number of visits to transit stations is decreasing. The positive shock in the transit station visits became also apparent in the regular gasoline model with a lag, and the diesel model also met this condition at least based on the 10% significance level. The negative shock on these fuel prices was significant at the 1% level, suggesting that regular gasoline and diesel also received a negative impact from negative changes in the transit station visits. These results imply that when the number of visits to transit stations is recovering, the fuel prices are increasing, but the fuel prices decrease when people start to refrain from visiting the stations in the short run. This result is opposite to the results of the long-run influence of the human mobility index of the transit stations. This is perhaps because the short-run coefficient does not reflect the shifts in the means of transportation and that the short-run coefficient only captures how a change from one period before influences the fuel price.

Table 7. NARDL model estimation.

| ΔPremium | | | ΔRegular | | | ΔDiesel | | | ΔKerosene | | |
|--------------------|--------|---------|-----------|--------------------|---------|-----------|-------|--------------------|-----------|-------|---------|
| Variables | Coef. | t-Stat. | Variables | Coef. | t-Stat. | Variables | Coef. | t-Stat. | Variables | Coef. | t-Stat. |
| Constant | −99.35 | *** | −3.09 | Constant | −65.53 | * | −1.83 | Constant | −63.90 | * | −1.96 |
| Premium(-1) | 0.58 | *** | 2.92 | Regular(-1) | 0.41 | * | 1.71 | Diesel(-1) | 0.46 | * | 1.85 |
| Transit+(-1) | 0.00 | | 0.09 | Transit+(-1) | 0.10 | | 1.34 | Transit+(-1) | 0.10 | | 1.41 |
| Transit(-1) | −0.53 | *** | −4.31 | Transit(-1) | −0.31 | ** | −2.43 | Transit(-1) | −0.32 | ** | −2.52 |
| Work+ ^a | 0.08 | | 1.28 | Work+(-1) | −0.05 | | −1.16 | Work+(-1) | −0.05 | | −1.08 |
| Work(-1) | 0.31 | *** | 3.46 | Work- ^a | 0.12 | ** | 2.61 | Work- ^a | 0.13 | *** | 2.87 |
| ΔPremium(-1) | −0.39 | * | −1.89 | ΔRegular(-1) | −0.15 | | −0.71 | ΔDiesel(-1) | −0.17 | | −0.77 |
| ΔPremium(-2) | −0.84 | *** | −4.36 | ΔRegular(-2) | −0.47 | ** | −2.24 | ΔDiesel(-2) | −0.46 | * | −2.00 |
| ΔTransit+ | 0.23 | ** | 2.17 | ΔTransit+ | 0.28 | | 2.09 | ΔTransit+ | 0.25 | * | 1.93 |
| ΔTransit+(-1) | 0.24 | ** | 2.70 | ΔTransit+(-1) | 0.20 | *** | 1.69 | ΔTransit+(-1) | 0.23 | * | 1.98 |
| ΔTransit+(-2) | 0.19 | ** | 2.25 | ΔTransit- | −0.41 | *** | −2.76 | ΔTransit- | −0.43 | *** | −2.97 |
| ΔTransit- | −0.40 | *** | −3.42 | ΔTransit(-1) | 0.14 | * | 1.91 | ΔTransit(-1) | 0.14 | * | 2.00 |
| ΔTransit(-1) | 0.25 | *** | 3.27 | ΔTransit(-2) | 0.10 | | 1.55 | ΔTransit(-2) | 0.11 | | 1.69 |
| ΔTransit(-2) | 0.16 | ** | 2.34 | ΔWork+ | 0.03 | | 0.53 | ΔWork+ | 0.04 | | 0.93 |
| ΔTransit(-3) | 0.09 | | 1.25 | ΔWork+(-1) | 0.05 | | 1.29 | ΔWork+(-1) | 0.04 | | 1.22 |
| ΔWork- | 0.08 | * | 2.00 | ΔWork+(-2) | 0.06 | ** | 2.04 | ΔWork+(-2) | 0.06 | ** | 2.13 |
| ΔWork(-1) | −0.14 | *** | −2.97 | EMG1 | 0.11 | | 0.07 | EMG1 | −0.06 | | −0.04 |
| ΔWork(-2) | −0.09 | ** | −2.74 | EMG2 | −2.30 | | −1.23 | EMG2 | −2.45 | | −1.38 |
| ΔWork(-3) | −0.05 | | −1.57 | | | | | | | | |
| EMG1 | −0.83 | | −0.80 | | | | | | | | |
| EMG2 | −4.78 | *** | −2.84 | | | | | | | | |

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. ^a Indicates the variable is interpreted as $Z = Z(-1) + \Delta Z$.

Coefficients of $\Delta Work(-1)$ and $\Delta Work(-2)$ for the premium gasoline model (significant at the 1% and 5% levels) reveal that the negative shocks in the visits to workplaces impact the gasoline price negatively. Although this effect is occurring with some lags, the result is consistent with the long-run coefficient of negative changes in the workplace visits having negative impacts on the fuel prices. This allows inferring that when people are working at home, the gasoline demand declines, which likely decreases the gasoline price.

Finally, Table 8 illustrates the results of the Breusch–Godfrey (BG) and the Breusch–Pagan (BP) tests. The Breusch–Godfrey test suggests that all models do not contain the serial correlation issue based on the 5% significance level. However, the Breusch–Pagan test demonstrated that although half of the models were homoscedastic, some of them were heteroskedastic when evaluated at the 5% significance level. To minimize the effects of the heteroscedasticity issue, the Newey–West heteroskedasticity and autocorrelation corrected (HAC) standard errors were applied.

Table 8. Serial correlation and heteroskedasticity tests.

| Model | BG F-Stat. | BP F-Stat. |
|--------------------|------------|------------|
| ARDL for premium | 1.05 | 2.29 |
| NARDL for premium | 2.24 | 2.27 |
| ARDL for regular | 1.35 | 1.38 |
| NARDL for regular | 1.61 | 0.79 |
| ARDL for diesel | 0.49 | 2.52 |
| NARDL for diesel | 1.37 | 0.85 |
| ARDL for kerosene | 0.71 | 2.26 |
| NARDL for kerosene | 0.29 | 1.74 |

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

Figures 3 and 4 are the plots of the CUSUM and CUSUMSQ tests. For the ARDL models, most of the CUSUM and CUSUMSQ statistics fell inside the 5% confidence intervals of parameter stability, suggesting that the coefficients in these models were stable. On the other hand, although the CUSUMSQ test indicated that all parameters are also stable in all the NARDL models, the CUSUM test for the NARDL kerosene model indicated that the parameters in this model were not stable. This instability in the parameters for the kerosene model might be the reason for the kerosene model having a cointegration relationship only at the 10% significance level.

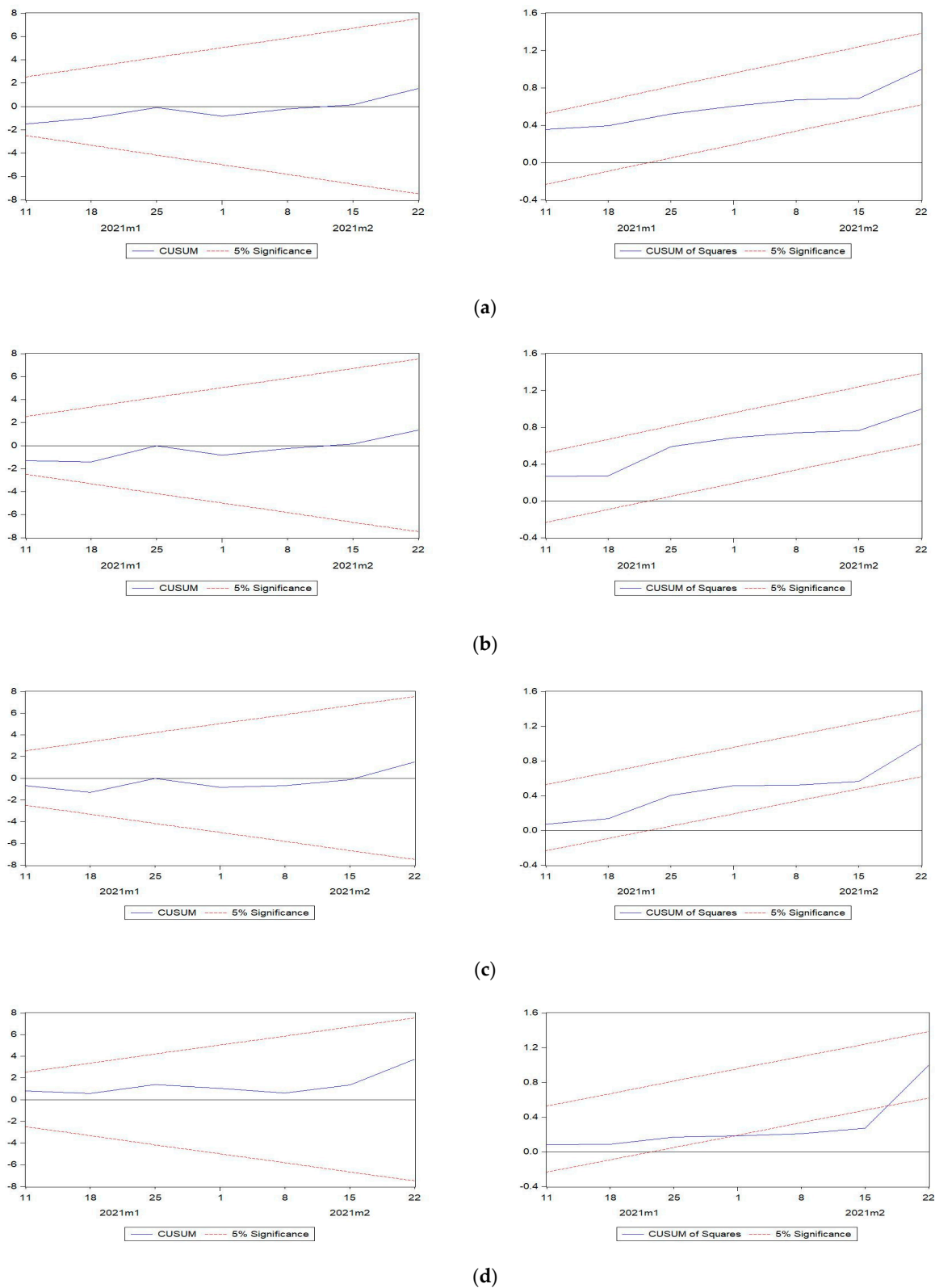
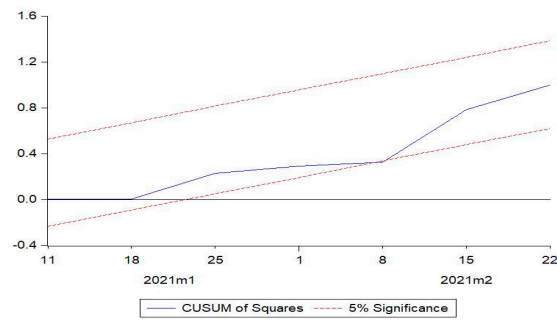
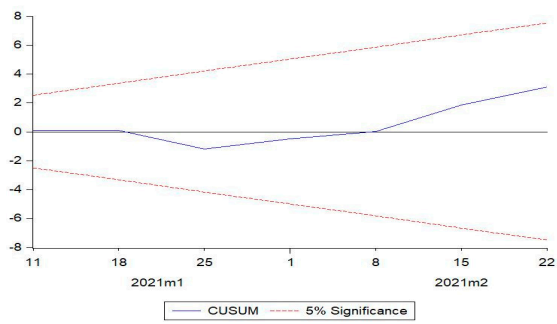
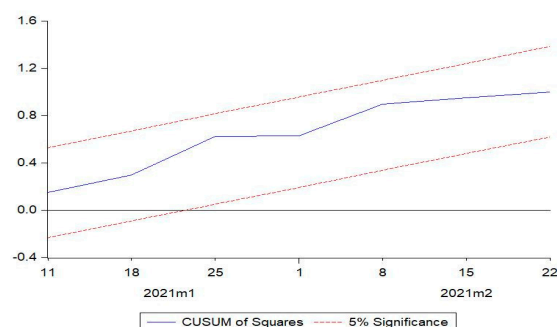
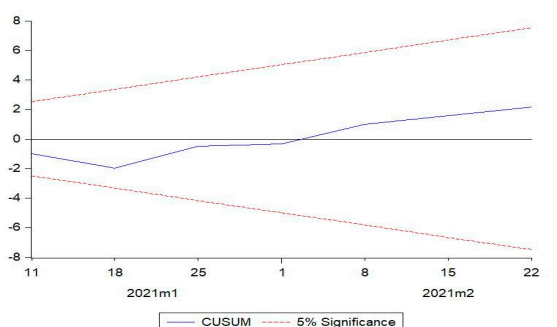


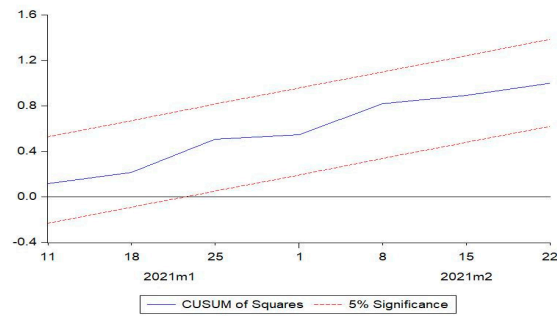
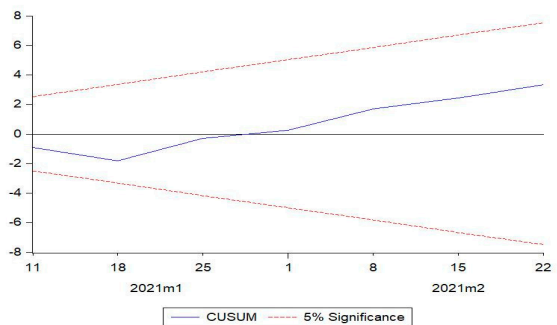
Figure 3. CUSUM and CUSUMSQR tests for the linear ARDL models. (a) Premium gasoline; (b) regular gasoline; (c) diesel; (d) kerosene.



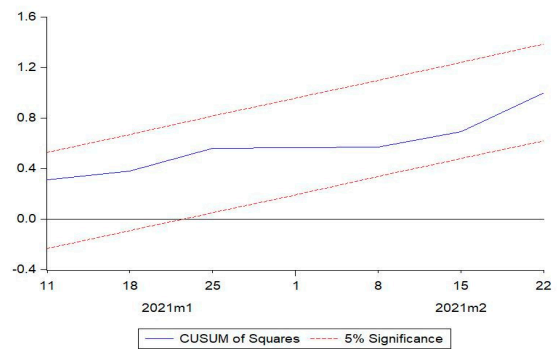
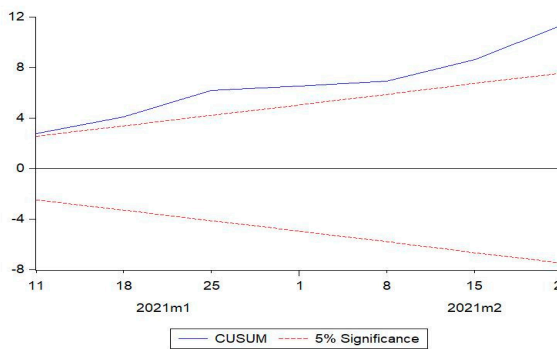
(a)



(b)



(c)



(d)

Figure 4. CUSUM and CUSUMSQ tests for the NARDL models. (a) Premium gasoline; (b) regular gasoline; (c) diesel; (d) kerosene.

4. Conclusions

This study investigated the effects of changes in human mobility during the COVID-19 pandemic on the Tokyo fuel markets. I analyzed the impacts of human mobility on the premium gasoline, regular gasoline, diesel, and kerosene prices for Tokyo. The effects of the changes in human mobility on these fuel prices were analyzed using indices reflecting the visits to transit stations and workplaces. The decline in the visits to transit stations had a positive impact in the long run, but the short-run effect suggested that the decline in the number of transit station visits affected the gasoline and diesel prices negatively. It was also found that when the number of workplace visits was decreasing, the premium gasoline price received a negative impact. Such reduced gasoline prices related to the drop in human mobility found in the case of Tokyo likely tell us that, similar to the previous studies conducted in other locations (Archer et al. 2020; Eisenmann et al. 2021), the COVID-19 pandemic has changed people's travel behavior. It is believable that in this study, the impact of COVID-19 on human mobility change became evident in the gasoline price being adversely impacted when human mobility was decreasing.

Overall, the study indicates that when the state of emergency lowers the number of people going out of their homes, the gasoline price will decline. In contrast, when the number of people going out recovers, the price will regain positive movement. Thus, the study reveals the tradeoffs of the state of emergency announcement. The government needs to implement strict stay-at-home orders to cope with the spread of the coronavirus, but this can hurt the economy because such orders will decrease human mobility. As the study identified that gasoline prices will face an adverse impact when human mobility decreases, it implies the importance of the government considering the provision of a subsidy for those working in the fuel retail industry that will likely receive damages when the government enforces stay-at-home orders. Thus, the study indicates that policymakers must prepare for an adverse impact on the fuel market when an extreme event like the COVID-19 pandemic will likely constrain human mobility.

This study is limited because the investigation had to be conducted using the data that were available at the time of the investigation. For example, more detailed data capturing the changes in human mobility at various locations might reveal a more precise influence of the effects of human mobility on the fuel markets. Furthermore, to examine the reasons behind the decline in the fuel price related to changes in human mobility, it would be helpful to conduct a household survey to identify the actual changes in the frequency of people going out of their homes during the pandemic and to find out if these changes influenced the demand on fuels investigated in the study.

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Data Availability Statement: Our data are freely downloadable from the homepages of the Agency for Natural Resources and Energy of the Ministry of Economy, Trade and Industry, Japan, and Our World in Data.

Conflicts of Interest: The author declares no conflict of interest.

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