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The Impact of Covid-19 Outbreak on Turkish Gasoline Consumption

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ABSTRACT

This paper investigates the effects of Covid-19 outbreak on Turkish gasoline consumption by employing a unique data set of daily data covering the 2014-2020 period. Forecast performance of benchmark ARIMA models are evaluated for both before and after the outbreak. Even the best-fit model forecasts fail miserably after the Covid-19 outbreak. Adding volatility improves forecasts. Consumption volatility increases due to the outbreak. Policies targeting volatility can reduce adverse impacts of similar shocks on market participants, tax revenues, and vulnerable groups.

Keywords: Gasoline Consumption, ARIMA Models, ARCH Family Models,

1. Introduction

The dynamics of energy markets have received great attention since the first oil crisis in 1970s when a sudden increase in oil price in response to a supply shock was observed (Akins, 1973). Sudden declines in energy prices also received attention as in the case of the first oil glut in 1980s (Fried, 1982) and in the case of oil price decline in 2014 (Ellwanger et al., 2017). Many studies were carried out to understand the reasons behind sudden and gradual fluctuations in both price and consumption. In high volatility periods market fundamentals were not sufficient in explaining oil price behavior. There are also studies that focus on consumption rather than prices. Demand for oil products is a main factor of fluctuations in the global oil market (Lynch, 2002). Bilgin and Ellwanger (2019) show that fuel consumption is very important in explaining elasticities in the global oil market. They point out that demand for oil may depend on the demand for oil products. They also emphasize the distinction between global and local markets. Fuel consumption forecasts help policy makers in pricing and taxation decisions, and in planning energy security. Consumption forecasts are also important to investors for making future investment decisions (Makridakis, Hogarth, & Gaba, 2009) (Kocherlakota, 2009). Furthermore, short run market disruptions in local fuel markets may have adverse effects on vulnerable groups in a society. Therefore, stability in local fuel markets is of high priority for policy makers.

The new oil glut has just started at the beginning of 2020 (Albulescu, 2020), with the spread of a new virus called Covid-19, namely Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-
CoV-2). The virus started to affect the world in a matter of weeks and became a pandemic, reducing both aggregate production and consumption globally. Although oil prices dropped to their lowest level for the last 18 years, demand still declines dramatically due to the pandemic and due to the policies followed to handle the pandemic (David, 2020). Impacts on local markets deserve a closer look, as they have an immediate impact on households and their dynamics may differ from the global markets.

The purpose of this paper is to examine the effects of Covid-19 outbreak on Turkish gasoline consumption. To that respect, we employ daily gasoline consumption and make forecasts for 40 day periods before and after the announcement of the first Covid-19 case in Turkey (March 10, 2020). We use ARMA and ARCH family models to reveal the disruptive effect of Covid-19 outbreak on the Turkish gasoline market. We evaluate the forecast performance of benchmark ARMA models in the face of the pandemic and select the best-fit model as a representative model used by market participants. We observe that consumption volatility increased significantly following the announcement. Volatility dynamics are important in explaining the increased uncertainty in response to the pandemic. Our results shed light on what to expect in the face of a similar shock in the future. Policy makers should develop immediate response plans that target consumption volatility to mitigate the adverse effects.

The paper is organized as follows: Section II introduces the overview of Turkish gasoline market, Section III presents literature review and Section IV presents data and methodology, Section V presents empirical results and Section VI concludes.

2. Turkish Automotive Gasoline Demand

The total number of vehicles running on gasoline is increasing slowly over the years in Turkey, estimated to be 2.8 million in 2014 and 3.0 million by the end of March 2020 with around 1% increase each year. (TSI, 2020) Likewise, gasoline consumption appears to follow a slow upward trend which is not significant. (EMRA, 2020)

*Figure 1 Daily Gasoline Consumption in Turkey Full Sample*
Daily gasoline consumption in Turkey over the past 5 years is presented in Figure 1. This is a unique data set, since energy consumption is usually not available in daily frequency. It enables us to see daily dynamics present in the consumption data. As can be seen from Figure 1, there is a seasonal trend in the gasoline fuel consumption; mainly increasing in summertime and decreasing during the winter. Moreover, the peaks in each year correspond to specific occasions such as the month of fasting and religious holidays namely, Ramadan, Eid al-Adha, etc. During these periods demand increases drastically for a short period of time since vacations up to 10 days during and after these periods increase the demand for travel. The 2020 data depicted in the figure below shows how the daily patterns changed after the Covid-19 outbreak more clearly.

**Figure 2 - Daily Gasoline Consumption in Turkey in 2020 (Gungor et al, 2020a)**
The daily seasonality is clearer in Figure 2. Therefore, there is not only weekly and yearly seasonality, but also daily seasonality in gasoline consumption. Furthermore, the impact of the first Covid-19 case announcement on March 10 (shown by the vertical line in Figure 2) is obvious. Initial immediate increase in consumption can be attributed to impulse purchases in response to a sudden increase in uncertainty. Then a steady declining trend governs the consumption behavior. It is also worth noting that the volatility dynamics of gasoline consumption also changed after March 10 (Güngör, Ertuğrul, & Soytaş, 2020). This calls for a more detailed examination of the volatility structure.

Covid-19 outbreak produced many adverse results in a very short time. It caused temporary shutdown of a fully operated refinery located in İzmir from 5th May 2020 to 1st July 2020. In addition, many oil stations lost their average sales by around 30% as we showed in our calculations, especially stations located in the intercity roads lost more than 30% due to travel bans to and from major cities where 65 million people live (about 80% of the population). This shrinkage in the gasoline market also affected the government budget in terms of indirect tax incomes. According to data gathered from (MoTaF, 2020), liquid fuel taxes constitute 10% to 18% of the total tax revenue in Turkey between 2002 and 2019. Therefore, this 30% shrinkage also reduces government income significantly. Policy makers need immediate action plans to mitigate the adverse effects of similar shocks in the future.

3. Literature Review

Consumption of energy products (oil, electricity etc) have been studied a lot over the last five decades. Many econometric applications were conducted to analyze the demand dynamics of energy products. For example, for Chinese electricity consumption forecasts (Zhu & Jianzhou
Wang, 2011) proposed an integration of the moving average procedure and seasonal autoregressive integrated moving average model (SARIMA) with weight coefficients. (Al-Qaness, Elaziz, & Ewes, 2018) used a modified data mining method, called as Sine-Cosine Algorithm adaptive neuro-fuzzy inference system (SCA-ANFIS) to forecast oil products’ consumption of Canada, Germany and Japan using the data from 2007 to 2018, containing 120 records per month for each country. (Öztürk & Öztürk, 2018) used energy consumption data from 1970 to 2015 to forecast energy consumption of Turkey for the next 25 years using ARIMA model. (Azadeh, Behmanesh, Arani, & Sadeghi, 2014, s. 5) on the other hand, used integrated fuzzy mathematical programming-regression-ANOVA approach to forecast gasoline consumption in selected countries (ISE, Canada, Japan, Iran and Kuwait) by using monthly data covering from 1992 to 2005. To project gasoline and diesel demand in India till 2025, (Agrawal, 2015) adopted a different perspective and considered both long and short run demand relations using the autoregressive distributed lag (ARDL) and error correction mechanism (ECM) co-integration procedures. (Bhutto and others, 2017) preferred a univariate approach and used Autoregressive Integrated Moving Average (ARIMA) model to forecast annual gasoline consumption in Pakistan. Their forecasts were demanded by policy makers planning to substitute in ethanol for gasoline. (Li, Wang, & Jianzhou Wang, 2018) considered 26 combination models based on an AI algorithm using traditional combination methods to forecast oil consumption in China. (Duan, Lei, & Shao, 2018) presented the grey-extended self-adapting intelligent grey model to predict the total crude oil consumption of China using 2002-2014 yearly data to forecast China’s 2015-2020 crude oil consumption. Moreover, (Li, Rose, & Hensher, 2010) provided an analysis of future gasoline demand in Australia by using eight models (partial adjustment model (PAM), ARIMA, Holt’s linear model, Holt-Winter’ model etc). They mainly concluded that more sophisticated models do not always produce better forecasting results than simple models. They advised to determine the characteristics of a time series before modelling and forecasting it. In this study we follow their suggestions.

There are a limited number of studies on Turkish gasoline consumption. Melikoglu (2014) forecasts that the annual gasoline consumption in Turkey could decline to 2.0 million m3 in 2023 in line with the government targets and European directives. Hasanov (2015) reports income and price inelastic quarterly demand for gasoline in Turkey. Also using quarterly data, Mikayilov et al. (2020) show that short run gasoline demand in Turkey is not sensitive to changes in income, prices, and car stock. This suggests that short run fluctuations may be driven by other factors in the short run. Gungor et al. (2020b) study the volatility dynamics of Turkish diesel consumption. They show that consumption volatility increased in response to the pandemic. This paper extends their discussion to gasoline consumption.

Most of the studies in the literature try to predict the annual or quarterly gasoline/diesel/crude oil consumption with a lot of assumptions and employing a variety of independent variables. The data frequencies are either yearly, quarterly or monthly in most of these studies. In this paper we employ daily data on Turkish gasoline consumption to better capture the short run dynamic impact of the pandemic on the market. Using high frequency data allows us not only to understand how rapidly consumption patterns changed, but also to examine what happened to market uncertainty via
consumption volatility. To the extent of our knowledge, this is the first study that focuses on daily consumption patterns in a local gasoline market.

4. Data and Methodology

In the empirical analysis, we use daily gasoline consumption in liters covering the 01.01.2014 - 19.04.2020 period. Table 1 presents descriptive statistics of the daily gasoline consumption of Turkey.

|                      | Gasoline Consumption (liters) |
|----------------------|------------------------------|
| **Mean**             | 8.056 million                |
| **Median**           | 7.836 million                |
| **Maximum**          | 22.315 million               |
| **Minimum**          | 1.142 million                |
| **Std. Dev.**        | 1.561 million                |
| **Skewness**         | 1.168                        |
| **Kurtosis**         | 9.302                        |
| **Jarque-Bera**      | 4332                         |
| **Observations**     | 2301                         |

According to Table 1, average daily gasoline consumption is 8.056 million liters and median value is 7.836 million liters within our sample period. Maximum and minimum values are 22.314 Million and 1.142 Million liters respectively, but standard deviation is 1.561 million. This implies that daily gasoline consumption does not vary a lot, but the high range indicates existence of occasional spikes. Moreover, normal distribution assumption is not valid for daily gasoline consumption according to Jarque-Bera test. For this reason, we consider alternative distributions in the empirical model. Positive skewness value for gasoline consumption indicates right skewed distribution, whereas the kurtosis value of 9.302 shows the fat tail characteristics of the daily gasoline consumption distribution.

We employ logarithmic difference (growth rate) of gasoline consumption data in order to ensure stationarity condition in the econometric modeling. Following the suggestion of (Li, Rose, & Hensher, 2010) we first check the stationarity properties of growth rates employing both conventional Ng-Perron unit root test and Zivot-Andrews (1992) and Lee-Strazicich (2003) structural break unit root test. We do not find any evidence of non-stationarity.

There are a variety of econometric methods one can use to forecast time series. A commonly used stochastic time series model is ARIMA (Autoregressive Integrated Moving Average) model. The univariate ARIMA models are simple and easy to estimate. They are usually used as benchmark models against which forecasting performances of alternative models are compared. Under certain conditions their forecasting performances are comparable to sophisticated models. These models analyze the stochastic properties of economic time series and use the history of the series itself instead of independent variables. In that respect these models can be viewed as a-theoretical and
suffer from omitted variable bias but adding independent variables may result in other complications such as endogeneity and multicollinearity. ARIMA models are the combination of differencing, moving average (MA) models and autoregressive (AR) models and mainly focus on lagged observations lagged dependent variables and error terms.

After stationarity checks, we estimate the best fit ARIMA structure for gasoline consumption data to compare forecasting performance of this benchmark model before and after the Covid-19 outbreak.

Then we investigate volatility dynamics of the daily gasoline consumption by using alternative ARCH family models. We estimate alternative ARCH family models including ARCH, GARCH, EGARCH and TGARCH models and we choose the best model according to forecast performance criteria. Then, we extract the conditional variance from the best fit model as consumption volatility.

Finally, we added the volatility variable to the best fit ARMA model as independent variable and assess how the forecast performance of the model is changing after Covid-19 outbreak when volatility variable is added.

5. Results

The forecasting models we consider require the time series to be stationary. Hence, we first investigate stationarity properties of growth rate of the gasoline consumption by using both conventional Ng-Perron unit root test and Zivot-Andrews (1992) structural break test for one break and Lee-Strazicich (2003) structural break unit root test for 2 breaks. Both Ng-Peron, Zivot Andrews (1992) and Lee-Strazicich (2003) tests indicate the stationarity of the growth rate of the gasoline consumption variable.\textsuperscript{4}

After stationarity checks, we estimate the best fit AR/ARMA structure for growth rate of the gasoline consumption for the 01.01.2014-10.03.2020 period. Table 2 presents alternative ARMA model results.\textsuperscript{5}

\textsuperscript{4} We did not add stationarity test results in order to save space. The results are available from authors upon request.
\textsuperscript{5} In order to estimate best-fit ARIMA model, we employ Box Jenkins 4 step procedure. We consider all possible models from SARMA(0,0)(0,0) to SARMA(7,7)(1,1) which makes 256 models and found out that the best 5 models according to LogL (Log Likelihood), AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion).
Table 2 - Alternative ARMA Model Results (01.01.2014 – 10.03.2020)

|         | ARMA(7,6) | ARMA(7,7) | SARMA(7,7)(1,1) | SARMA(7,6) (1,1) | SARMA(1,1) (7,7) |
|---------|-----------|-----------|----------------|-----------------|-----------------|
| AR(1)   |           |           |                | (0.445)*        |                 |
| MA(1)   |           |           |                |                 | (0.849)*        |
| AR(7)   | (0.470)*  | (0.999)*  | (0.999)*       | (0.475)*        |                 |
| MA(6)   | (0.099)*  |           |                | (0.078)*        |                 |
| MA(7)   |           | (-0.987)* | (-0.988)*      |                 |                 |
| SAR(1)  |           |           | (0.445)*       | (0.558)*        |                 |
| SMA(1)  |           |           | (-0.849)*      | (-0.959)*       |                 |
| SAR(7)  |           |           |                | (0.999)*        |                 |
| SMA(7)  |           |           |                |                 | (-0.988)*       |
| C       | 0.001     | 0.004     | 0.001          | 0.001           | 0.001           |

Model Selection Criteria and Diagnostic Checks

|         | AIC       | SC        | $\chi^2_{BG}$ |
|---------|-----------|-----------|---------------|
|         | -2.027    | -2.020    | 74.832[0.000] |
|         | -2.313    | -2.305    | 179.463[0.000]|               |
|         | -2.528    | -2.515    | 0.772[0.379]  |               |
|         | -2.234    | -2.221    | 1.464[0.219]  |               |
|         | -2.527    | -2.514    | 0.774[0.379]  |               |

Forecast Performance (Estimation 01.01.2014-30.01.2020 - Forecast 31.01.2020-3.10.2020)

|         | RMSE      | MEA       | MAPE    | Theil    |
|---------|-----------|-----------|---------|----------|
|         | 652890    | 501729    | 6.077   | 0.040    |
|         | 456469    | 353847    | 4.451   | 0.027    |
|         | **446235**| **348866**| **4.351**| **0.026**|
|         | 634289    | 513418    | 6.397   | 0.039    |
|         | 465563    | 358591    | 4.527   | 0.028    |

Notes: Five estimated models include ARMA(7,6), ARMA(7,7), SARMA(7,7)(1,1), SARMA(7,6) (1,1), and SARMA(1,1) (7,7). Only statistically significant coefficients are displayed in the table. * indicates significance at the 1% level. AIC and SC represent Akaike Information Criterion and Schwartz Criterion, respectively $\chi^2_{BG}$ denotes $\chi^2$.
Breusch-Godfrey test statistic which follows a $\chi^2$ distribution. RMSE is root mean square error, MEA is mean absolute error, MAPE is mean absolute percentage error, Theil stands for the Theil inequality index.

According to Table 2, both ARMA(7,6) and ARMA(7,7) models exhibit severe autocorrelation problems and we omit these models. Seasonal ARMA (SARMA) models seem to have better fits due to the apparent seasonality in the series. SARMA(7,7)(1,1) model is found to be the best fit model for gasoline demand variable according to both model selection criteria and forecast performance criteria.

After we define best fit model for the full sample, we make forecasts for periods before and after Covid-19 outbreak in Turkey (March 10, 2020) to indicate how Covid-19 outbreak distorts forecast performance of the models.

For this reason, we estimate the model for the 01.01.2014-30.01.2020 period and forecast for the 31.01.2020-10.03.2020 (40 days) period to assess the forecast performance of the model. Then, we estimate the model for the 01.01.2014-10.03.2020 period and forecast for the 11.03.2020-19.04.2020 (40 days) period to analyze the forecast performance of the model after Covid-19 outbreak. This enables us to compare our 40-day forecasts before and after our Covid-19 break date, March 10, 2020. Before and after forecasts along with actual data are displayed in Figures 3 and 4, respectively.

**Figure 3 - Forecasts Before Covid-19 Outbreak**
Figure 3 and Figure 4 indicate how Covid-19 outbreak distorts the forecast performance of the best fit SARMA(7,7)(1,1) model. Before Covid-19 outbreak, there is only 0.8% difference between actual and forecasted gasoline consumption data. On the other hand, Figure 4 shows that there is an approximately 30% difference between actual and forecasted total gasoline consumption data after Covid-19 outbreak.
The consumer behavior has revealed a very different situation than expected with the government sanctions due to the volatility observed in consumptions since the first appearance of the Covid-19 case in Turkey. Gasoline demand dynamics after the first case in Turkey are uncommon compared to historical movements. A downward trend and increased volatility seem to govern demand dynamics in this period following a temporary initial jump. Hence, models that rely on historical data will have very poor forecast performances for this period. These data indicate how oil markets are shrinking in response to a global health crisis.

In the second part of our analysis, we investigate volatility dynamics of the gasoline consumption data. We estimate alternative ARCH family models including ARCH, GARCH, EGARCH and TGARCH models by employing best fit ARMA model as mean equation for 01.01.2014-19.04.2020 periods\(^6\). Then we choose the best model according to several forecast performance criteria. Table 3 presents the results of the alternative volatility models.

### Table 3 – Volatility Model Results

|                  | ARCH(1)       | GARCH(1,1)   | TGARCH(1,1)  | EGARCH(1,1)  |
|------------------|---------------|--------------|--------------|--------------|
| **Mean Equation**|               |              |              |              |
| AR(7)            | (0.999)*      | (0.999)*     | (0.999)*     | (0.999)*     |
| SAR(1)           | (0.407)*      | (0.401)*     | (0.526)*     | (0.525)*     |
| MA(7)            | (-0.983)*     | (-0.983)*    | (-0.983)*    | (-0.982)*    |
| SMA(1)           | (-0.840)*     | (-0.823)*    | (-0.855)*    | (-0.850)*    |
| C                | (-0.043)      | (-0.022)     | (0.002)      | (0.005)      |
| **Variance Equation** |           |              |              |              |
| \(\varepsilon_{t-1}^2\) | (0.171)*     | (0.150)**    | (0.702)*     |              |
| \(h_{t-1}\)     | (0.600)*      | (0.257)*     |              |              |
| \(I_{t-1}\)     | (0.438)*      |              |              |              |
| \(\frac{\varepsilon_{t-1}}{h_{t-1}}\) |              |              | (-0.130)*    |              |
| \(\frac{|\varepsilon_{t-1}|}{h_{t-1}}\) |              |              | (0.559)*     |              |
| \(lnh_{t-1}\)   |                |              | (0.723)*     |              |
| C                | (0.015)*      | (0.014)*     | (0.001)*     | (-2.047)*    |

### Model Selection Criteria Results

\(^6\) We use student t distribution instead of normal distribution because of the Jarqua-Bera test results presented.
AIC | -2.012 | -2.303 | **-2.899** | -2.881
---|---|---|---|---
SC | -1.992 | -2.281 | **-2.877** | -2.858

**Forecast Performance (Estimation 01.01.2014-30.01.2020 Forecast 31.01.2020-3.10.2020)**

|        | RMSE    | MEA     | MAPE   | Theil   |
|--------|---------|---------|--------|---------|
| 01.01.2014-30.01.2020 | 448628  | 356854  | 4.409  | 0.028   |
| 31.01.2020-3.10.2020  | 449189  | 351654  | 4.399  | 0.027   |
|                  | **447458** | **350794** | **4.384** | **0.027** |

**Notes:** *, ** denote significance at the 1% and 5% levels, respectively. Variance equations are as follows. ARCH: $h_t^2 = a_0 + \sum_{i=1}^q a_i \varepsilon_{t-i}^2$. GARCH: $h_t^2 = a_0 + \sum_{i=1}^q a_i \varepsilon_{t-i}^2 + \sum_{j=1}^p b_j h_{t-j}^2$. TGARCH: $h_t^2 = a_0 + \sum_{i=1}^q (a_i + \gamma \varepsilon_{t-i}) \varepsilon_{t-i}^2 + \sum_{j=1}^p b_j h_{t-j}^2$. EGARCH: $\ln h_t^2 = a_0 + b_1 \ln h_{t-1}^2 + \alpha \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta \frac{\varepsilon_{t-1}}{h_{t-1}}$. RMSE is root mean square error, MEA is mean absolute error, MAPE is mean absolute percentage error, Theil stands for the Theil inequality index.

TGARCH(1,1) model performs as the best model according to both model selection and forecast performance criteria. The conditional heteroscedasticity of the best fit model is taken as the volatility of Turkish gasoline consumption. Conditional heteroscedasticity obtained from TGARCH(1,1) model is presented in Figure 5.

**Figure 5 - Volatility Variable Obtained from TGARCH(1,1) Model**

As seen in Figure 5, the uncommonly high volatility starts after March 11, 2020, which is the day after of the first Covid-19 case announcement. Later on, the volatility value reaches its peak in the middle of April, 2020 due to new sanctions of the government, such as weekend curfews and bans on some intercity travels.
Finally we added volatility variable to SARMA(7,7)(1,1) model as independent variable and investigate how forecast performance change after adding volatility variable to the best fit ARMA model to have a GARCH in mean model. We have already established that Covid-19 outbreak distorts the gasoline consumption forecasts for the 11.03.2020-19.04.2020 period. We employ SARMA(7,7)(1,1) model with and without volatility variables and estimate the model for the 01.01.2014-10.03.2020 period and forecast for the 11.03.2020-19.04.2020 period. Forecast performance comparison of the SARMA(7,7)(1,1) model with and without volatility variable for 11.03.2020-19.04.2020 period are presented in Table 4.

Table 4 - Forecast Performance Comparison of the Best Fit Model with and without Volatility Variable After Covid-19 Outbreak

|                      | SARMA(7,7)(1,1)- Without Volatility | SARMA(7,7)(1,1)- With Volatility |
|----------------------|--------------------------------------|----------------------------------|
| RMSE                 | 3509168                              | 3463934                          |
| MEA                  | 2795437                              | 2663320                          |
| MAPE                 | 88.484                               | 41.341                           |
| Theil                | 0.231                                | 0.192                            |

Notes: RMSE is root mean square error, MEA is mean absolute error, MAPE is mean absolute percentage error, Theil stands for the Theil inequality index.

Table 4 indicates that volatility variable increase the forecast performance of the best fit SARMA(7,7)(1,1) model. Figure 6 presents the actual gasoline consumption data and forecasts obtained from SARMA(7,7)(1,1) model with and without volatility variables.
Figure 6 - Forecasting Graph with and without Volatility Variable After Covid-19 Outbreak

Figure 6 also indicates that forecast performance of the SARMA(7,7)(1,1) model increase when we take the conditional variance into account. For the first couple of days following the announcement of the first case the no-volatility model forecasts appear to be closer to actual values, but these days are governed by impulse purchases due to panic and the phenomenon does not last long. The increase in the volatility due to Covid-19 outbreak hampers the prediction performance of the best fit model. This shows that increased uncertainty must be accounted for in the model to improve the forecast performance.

6. Conclusions

In this paper, we examined the effect of Covid-19 outbreak on daily Turkish gasoline consumption covering the 01.01.2014 - 19.04.2020 period. Initial response to the announcement of the first case on March 10, 2020 shows a short-lived positive spike followed by a steady downward trend around which an uncommonly high volatility is observed. We evaluate the forecast performance of benchmark ARIMA models both before and after the outbreak. While the best fit model forecasts fail miserably after the announcement, when the changes in the volatility structure of daily gasoline consumption is considered, the forecast performance improves. We next summarize the empirical steps.
In the empirical analyses, we first checked stationarity of growth rate of the gasoline consumption of Turkey. Then, we determine the best fit AR/ARMA structure that we can assume the market participants use to forecast growth rate of gasoline consumption. SARMA(7,7)(1,1) model is the best-fit model according to both model selection and forecast performance criteria. Then, we forecast gasoline consumption 40 days before and 40 days after first Covid-19 case announcement in Turkey (10 March 2020) in order to indicate how Covid-19 outbreak distorts forecasting ability of market participants. We find that, before the outbreak, there is only %0.8 difference between actual and forecasted gasoline consumption data. On the other hand, there is approximately a 30% difference ta after the outbreak. Next, we examined the volatility dynamics of the gasoline consumption. We find that TGARCH(1,1) model is the best model according to both model selection and forecast performance criteria. We derive the conditional heteroscedasticity of the best fit model as the volatility of Turkish gasoline consumption. We observe that gasoline consumption volatility intensifies significantly after the outbreak. The high volatility episode starts on March 11, 2020, which is the day after the announcement of the first Covid-19 case. Later on, the volatility value reaches its peak in mid-April due to new sanctions imposed by the government, such as weekend curfews and intercity travel bans. Finally, we added volatility variable to SARMA(7,7)(1,1) model as independent variable and investigate how forecast performance change after adding volatility variable to the best fit ARMA model and found that forecast performance of the SARMA(7,7)(1,1) model increase after we add volatility variable as independent variable. We show that the increase in the volatility due to Covid-19 outbreak causes distortion in the prediction performance of the best-fit model.

Our main conclusion is that in response to similar shocks policy makers should design policy responses that target consumption volatility to stabilize the market. This will reduce the uncertainty faced by market players, stabilize tax revenues, and protect vulnerable groups. Secondly, policy makers and traders should avoid using benchmark models to predict energy use during similar crisis. They should consider models that capture the increased volatility structure. Although countries try to adopt policies to put their economies on track, conventional economic policies are not likely to have a significant impact on energy markets in the short run. This is because the short run energy consumption behavior is likely to be driven by measures taken by government authorities to contain the pandemic (e.g. curfews, travel bans), by social behavior (e.g. social distancing, work from home, online meetings), and by market expectations (e.g. hoarding). Although government measures can be lifted overnight, social behavior and expectations may last longer. In order to relieve the disruptive effects of Covid-19 pandemic, we make two proposals: temporary rearrangement of profit margins of the dealers and liquid fuel distributors and a temporary tax regulation throughout the year to compensate the tax revenue lost. Such measures are expected to reduce volatility in gasoline consumption, stabilize the market, and mitigate the decline in tax revenues. Reduced volatility can benefit energy poor households who tend to make low volume but high frequency purchases. It would be illuminating to examine the results of these measures in the near future as the pandemic and responses to the pandemic evolves.
ANNEX:

ARIMA Model:

ARIMA method, as known as Box-Jenkins methodology, is one of the most widely used forecasting methods for univariate time series data forecasting. AR(p), MA(q) and ARMA(p,q) models are based on stationary time series. If the time series data is non-stationary ARMA model, giving a differenced $d$ times before it becomes stationary, as non-seasonal ARIMA $(p,d,q)$ model, which can be written as:

$$\nabla^d Y_t = \delta + \theta_1 \nabla^d Y_{t-1} + \theta_2 \nabla^d Y_{t-2} + \cdots + \theta_t - \varphi_1 \beta_{t-1} - \varphi_2 \beta_{t-2} - \cdots - \varphi_q \beta_{t-q}$$

(1)

As a short version, ARIMA$(p,d,q)$ model in lag $(L)$ operator form can be written as:

$$\theta_p(L)(1 - L)^d Y_t = \delta + \varphi_q(L) \beta_t$$

(2)

where $\beta_t$ is white noise, $L$ is the backshift operator $(LY_t = Y_{t-1})$, $\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_p L^p$ and $\varphi(L) = 1 - \varphi_1 L - \varphi_2 L^2 - \cdots - \varphi_q L^q$ are the polynomials of orders $p$ and $q$ respectively.

But this method does not support seasonable components, in other words time series with a repeating cycle, and a tweak is required to handle and give such a support to ARIMA, which is called Seasonal ARIMA. Similarly, a seasonal ARIMA (SARIMA) model is the most common model used in many applications in industries, economics and financial. (Tseng & Tzeng, 2002)

There are some new hyperparameters to the components of ARIMA in SARIMA model, named as seasonal autoregression (SAR), differencing (D) and seasonal moving average (SMA), as well an additional parameter for the period of the seasonality. (Athanasopoulos & Hyndman, 2013)

It is mainly represented by ARIMA$(p,d,q)(P,D,Q)_s$; where $p, q, d$ were discussed before, the next terms $(P,D,Q)_s$ represents seasonal parameters and lastly $s$ indicates seasonal length in the data.

In the lag operator, if we transform ARIMA into polynomial form of the SARIMA, the equation (3) can be written as:

$$\theta_p(L)\theta_p(L^s)L^s(1 - L)^d(1 - L^s)^D Y_t = \delta + \varphi_q(L)\varphi_q(L^s)\beta_t$$

(3)

where blue parts in the equation (3) shows the new terms in the ARIMA to transform the model into SARIMA. (Camara, Feixing, & Xiuqin, 2016) In order to estimate the best SARIMA model for gasoline consumption data, the non-seasonal and seasonal components of autoregressive and moving average parameters must be estimated. To do so, the information criteria, such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and the Hannan – Quinn criterion (HQ) are used to determine the best model.
Conditional Variance Models (Volatility Models)

ARCH Model:
In econometrics, the concept of conditional variance was used for the first time in the literature by (Engle, 1982). Engle modeled conditional variance as a function of the past values of error term and defined the autoregressive conditional variance model as follows [ARCH(q)]:

\[
\varepsilon_t = v_t h_t \\
h_t^2 = a_o + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2
\]

(4)

Therefore, ARCH[1] can be expressed as:

\[
\varepsilon_t = v_t \sqrt{a_o + a_1 \varepsilon_{t-1}^2}
\]

(5)

where \( v_t \) is the white noise error term distributed as N(0,1) and \( Var(v_t) = 1 \). Moreover, \( a_o \) and \( a_1 \) are constant where \( a_o > 0 \) and \( 0 < a_1 < 1 \).

GARCH Model:
One of the biggest problems of the ARCH model is that it is possible too many past values of error terms could be found statistically significant. In order to solve this problem, (Bollerslev, 1986) proposed Generalized Autoregressive Conditional Variable Variance (GARCH) model. GARCH(p,q) can be expressed as:

\[
\varepsilon_t = v_t h_t \\
h_t^2 = a_o + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} b_j h_{t-j}^2
\]

(6)

Therefore, GARCH[1,1] can be expressed as;

\[
\varepsilon_t = v_t \sqrt{a_o + a_1 \varepsilon_{t-1}^2 + b_1 h_{t-1}^2}
\]

(7)

TGARCH Model:
Standard ARCH / GARCH models don’t take asymmetry into consideration. In ARCH/GARCH models, only the magnitude of the shock is important. Its sign is ignored. TGARCH model proposed by (Glosten, Jagannathan, & Runkle, 1993) investigate the effect of asymmetry on volatility. TGARCH model specification is presented below:

TGARCH model proposed by is presented below;

\[ h_t^2 = a_0 + \sum_{i=1}^{q} (a_i + \gamma I_{t-i}) \epsilon_{t-i}^2 + \sum_{j=1}^{p} b_j h_{t-j}^2 \]  

(8)

So TGARCH(1,1) can be express as;

\[ \epsilon_t = \nu_t \sqrt{a_o + a_1 \epsilon_{t-1}^2 + b_1 h_{t-1}^2 + \gamma I_{t-1} \epsilon_{t-1}^2} \]

(9)

\[ I_{t-1} = \begin{cases} 1, & \epsilon_{t-1} < 0 \\ 0, & \epsilon_{t-1} \geq 0 \end{cases} \]

The only difference between TGARCH(1,1) and GARCH(1,1) model is the \( \gamma I_{t-1} \epsilon_{t-1}^2 \) term in equation (9). The function \( I_{t-1} \) is an indicator function to help to model the asymmetry. Positive asymmetry parameter \( \gamma \) indicates that asymmetry is present.

**EGARCH Model:**

EGARCH model proposed by Nelson (1991) was defined as logarithmic and by doing so negative parameter values are prevented. Thus, the coefficients could take negative values.

EGARCH (1,1) is expressed as:

\[ \epsilon_t = \nu_t h_t \]

\[ \ln h_t^2 = a_0 + b_j \ln h_{t-1}^2 + a \frac{\epsilon_{t-1}}{h_{t-1}} + \beta \frac{\epsilon_{t-1}}{h_{t-1}} \]  

(10)

EGARCH model takes the asymmetry into consideration.
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