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# The Effect of Covid-19 Outbreak on Turkish Diesel Consumption Volatility Dynamics

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## ABSTRACT

We analyze the effect of the COVID-19 outbreak on volatility dynamics of the Turkish diesel market. We observe that a high volatility pattern starts around mid-April, 2020 and reaches its peak on 24/05/2020. This is due to the government imposed weekend curfews and bans on intercity travels. Two policy suggestions are provided. First is a temporary rearrangement of profit margins of dealers and liquid fuel distributors; and, second is a temporary tax regulation to compensate lost tax revenue.

Keywords: Diesel Consumption, ARIMA Models, ARCH Family Models, Covid-19 pandemic.

## 1. Introduction

Energy is a necessity for societies and its security and accessibility is a priority for policy makers. One of the main sources of energy has been oil and oil products since the middle of 19<sup>th</sup> century and its importance is not fading away soon. Hence, movements in oil prices have also been an important factor that needs to be closely followed. It has been half a century since the first oil crisis with a sudden quadruple increase in oil prices in 1970s that attracted a lot of attention in both empirical and theoretical economics (Akins, 1973). Likewise, the sudden price decreases have also received interest as in the case of the first oil glut in 1980s (Fried, 1982). Many studies were carried out in the literature to explain the abrupt and gradual rises and falls in energy prices (Kocherlakota, 2009).

Energy consumption and production forecasts were made with special attention to oil crises and oil gluts over the last 50 years. Many econometric applications were conducted to analyze the demand dynamics of various oil products and to forecast consumption. For example, for Chinese electricity consumption forecasts, Zhu et al. (2011) proposed an integration of the moving average procedure and seasonal autoregressive integrated moving average model (SARIMA) with weight coefficients. J. Li et al. (2018), on the other hand, considered more than 20 combination models using traditional combination methods to forecast oil consumption in China. Rashid and Kocaaslan (2013) examined the relationship between energy consumption volatility and unpredictable variations in real GDP by estimating a Markov switching autoregressive conditional heteroskedasticity (ARCH) model for the UK. In addition, Z. Li et al. (2010) provided an analysis of future gasoline demand in Australia by using various models. They found that more sophisticated models do not always produce better forecasting results compared to simple models. They advised to determine the characteristics of time series data before modelling and forecasting them. Their suggestions were followed by Agrawal (2015) who employed an autoregressive distributed lag based co-integration model in order to forecast gasoline and diesel demand for

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India. In a similar fashion, but with a simpler model, Bhutto et al. (2017) forecasted annual gasoline consumption for Pakistan. Given this literature, one research gap is that there are no studies that examine how energy consumption volatility changes in the face of a global pandemic. This study aims to fill this gap by studying the Turkish diesel market during the recent COVID-19 pandemic.[1] In addition, we also show how the pandemic distorts the forecasting performance of models.

The fluctuations in oil prices started at the beginning of 2020 with the spread of COVID-19. Volatility in energy markets increased. We add to the understanding of energy markets by examining the effect of the COVID-19 pandemic on diesel consumption. Our paper is the first to investigate volatility dynamics of the diesel consumption in light of the global pandemic.

The purpose of this paper is to examine the effects of the COVID-19 pandemic on the Turkish diesel market and assess the performance of simple forecasting tools. To achieve this aim, we employ variants of the generalized ARCH (GARCH) models. These models allow us to investigate the disruptive effects of the pandemic on the Turkish diesel market. We find that volatility starts rising with the announcement of the first case and peaks at the end of May 2020. Even though purchases increase in the 2 days following the announcement, they then assume a steady downward trend.

The paper is organized as follows: Data and methodology are presented in section 2 and results are presented in section 3. Section 4 concludes.

## **2. Data and Methodology**

In the empirical modeling, we use daily diesel consumption. Data cover the 01/01/2014 - 15/06/2020 period. Diesel consumption data are obtained from the Energy Market Regulatory Authority database. Descriptive statistics of the daily diesel consumption of Turkey are presented in Table 1.

The data suggest that the average and median daily diesel consumption are 48.8 and 49.2 million liters, respectively, while the maximum and minimum values are 22.3 and 6.2 million liters, respectively. The standard deviation stands at 10.01 million liters. This implies that daily diesel consumption varies a lot in our sample period. Moreover, the Jarque-Bera test rejects the null hypothesis of a normal distribution for daily diesel consumption. Negative skewness value for diesel consumption indicates left skewed distribution, whereas the kurtosis value of 3.242 indicates the fat tail characteristic of diesel consumption.

In order to ensure the stationarity condition, we employ logarithmic difference (growth rate) of diesel consumption data. We first investigate the stationarity of diesel consumption growth rate using both the conventional Ng-Perron unit root test and Zivot- Andrews (1992) structural break unit root test and found stationarity of the diesel consumption data.

For empirical analysis, in order to obtain the conditional heteroscedasticity (volatility) of the daily diesel consumption data, we limit ourselves to simple univariate models that have comparable performances with more sophisticated models as shown in the literature. We first estimate the best fit ARIMA structure for the mean equation.

Next, we estimate alternative GARCH type models in order to analyze volatility dynamics of the daily diesel consumption. These models include ARCH, GARCH, Exponential GARCH (EGARCH) and Threshold GARCH (TGARCH), and the best model is determined based on information criteria and forecast performances.[2] Then, we obtain the conditional variance from the selected model as daily diesel volatility.

### **3.Results**

After confirming stationarity, SARMA(7,7)(1,1) model is found to be the best model for daily diesel consumption according to model selection and forecast performance criteria<sup>3, 4</sup> .

After we define the mean equation, we analyze volatility dynamics of the daily diesel consumption variable by employing alternative ARCH family models including ARCH, GARCH, EGARCH and TGARCH models<sup>5</sup> . We define the best volatility model by comparing the forecast performances of the models<sup>6</sup> . Table 1 presents the results of the alternative volatility models.

Table 1 indicates that the TGARCH(1,1) model is the best performing model according to both model selection and forecast performance criteria. The conditional heteroscedasticity of the selected model is taken as a proxy for the Turkish diesel consumption volatility. Volatility dynamics over time is presented in Figure 1.

As seen in Figure 1, the uncommonly high volatility starts after 11/03/2020, which is the day after the first COVID-19 case was announced in Turkey. The volatility value reaches its peak in mid-April 2020 due to new sanctions imposed by the government, such as the weekend curfews and intercity travel restrictions. As of 11/03/2020, when the pandemic started, there was a significant increase in diesel consumption volatility. Uncertainty driven initial purchases of diesel were followed by a steady decline in consumption. Volatility reached highest levels during curfews, fell in response to normalization policies in Turkey, and converged to 0 over time.

### **6. Conclusion**

In this note, we employ a SARMA(7,7)(1,1) model and the TGARCH(1,1) model to represent and variance of the Turkish diesel consumption. We find that a phase of high volatility starts after mid-April 2020 and peaks on 24/05/ 2020. A 29% decrease in diesel sales is observed between 10/03/2020 and 01/06/2020. Volatility declines after 01/06/ 2020 consistent with a return to normalcy. Shrinkage in the diesel market has an important adverse effect on indirect tax revenues. We make two policy suggestions to mitigate the disruption in the market. First, we suggest a temporary rearrangement of profit margins of dealers and distributors. Second, we suggest enactment of a temporary tax regulation to compensate for lost tax revenue.

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**Table 1 – Volatility Model Results**

	ARCH(1)	GARCH(1,1)	TGARCH(1,1)	EGARCH(1,1)
<b>Mean Equation</b>				
AR(7)	0.998*	0.998*	0.998*	0.998*
SAR(1)	0.629*	0.650*	0.676*	0.662*
MA(7)	-0.987*	-0.863*	-0.989*	-0.923*
SMA(1)	-0.874*	-0.906	-0.880*	-0.881*
<b>Variance Equation</b>				
$\varepsilon_{t-1}^2$	0.833*	0.514*	0.385*	
$h_{t-1}$		0.325*	0.423*	
$I_{t-1}$			0.243*	
$\frac{\varepsilon_{t-1}}{h_{t-1}}$				-0.078
$\left  \frac{\varepsilon_{t-1}}{h_{t-1}} \right $				0.699*
$\ln h_{t-1}$				0.232*
C	0.001	0.001	0.001	0.705
<b>Model Selection Criteria Results</b>				
AIC	-3.144	-3.047	<b>-3.164</b>	-3.104
SC	-3.127	-3.028	<b>-3.142</b>	-3.082
<b>Forecast Performance (Estimation 01.01.2014-30.01.2020 Forecast 31.01.2020-3.10.2020)</b>				
RMSE	4729051	4597081	<b>3360312</b>	3944596
MEA	3699032	3594395	<b>2698345</b>	2919957
MAPE	7.056	6.867	<b>5.228</b>	5.812
Theil	0.047	0.046	<b>0.033</b>	0.038

**Notes:** \* indicates significance at the 1% level. AIC and SC represent Akaike Information Criterion and Schwartz Criterion, respectively. RMSE is root mean square error, MEA is mean absolute error, MAPE is mean absolute percentage error, Theil stands for the Theil inequality index.

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

VOL\_TGARCH

