Intervention Analysis of COVID-19: Implications for Fuel Prices in Ghana

Christian Akrong Hesse[1], Dominic Buer Boyetey[2], Emmanuel Dodzi Kpeglo[3*], Saralees Nadarajah[4]

[1]Department of Economics and Actuarial Science, University of Professional Studies, Accra, Ghana, christian.hesse@upsamail.edu.gh

[2]Department of Built Environment, University of Environment and Sustainable Development, Ghana, dbboyetey@uesd.edu.gh

[3]Department of Economics and Actuarial Science, University of Professional Studies, Accra, Ghana, emmanuel.kpeglo@upsamail.edu.gh

[4]Department of Mathematics, University of Manchester, United Kingdom, mbbsssn2@manchester.ac.uk

Corresponding author: Emmanuel Dodzi Kpeglo

Abstract

The COVID-19 pandemic has affected health systems and economies worldwide, particularly the energy industry. As in many other countries, the energy industry in Ghana suffered major fallout as increasing uncertainty and dramatic swings in global fuel demand became key drivers. Fuel was an essential input that enabled economic activities to continue operating during the period of mobility restrictions. The objective of this study is to examine the effects of the COVID-19 pandemic on fuel prices in Ghana from January 2016 to April 2023. An autoregressive integrated moving average model under the Box–Tiao intervention framework is used, with January 2021 taken as an intervention point corresponding to the structural change related to the loosening of pandemic-related mobility restrictions. Data from the pre-intervention period (2016–2020) are utilised to assess the fundamental dynamics of fuel prices and to produce counterfactual projections for the post-intervention phase. The COVID-19 effect is identified as the deviation between observed fuel prices and the predicted counterfactual path implied by the pre-pandemic ARIMA structure. The results suggest a statistically significant increase in the mean fuel price after the intervention. The estimated average causal effect is GH¢4.36 per litre. This means a relative increase of about 87% compared to the counterfactual scenario. The findings provide empirical evidence that the dynamics of fuel prices in Ghana underwent a structural change due to pandemic-related mobility restrictions and their

subsequent relaxation. The research demonstrates the efficacy of intervention time-series models to identify the economic consequences of significant external shocks in emerging energy markets.

Keywords: COVID-19, fuel price, intervention analysis, travel restrictions, Ghana

Introduction

The year 2020 marked a significant period in global health history, as the World Health Organization (WHO) declared COVID-19 a pandemic (Heyden & Heyden, 2021). By the end of January 2020, the virus had spread to 100 countries, with over 500,000 confirmed cases and 10,000 reported deaths (WHO, 2020). This situation led to worldwide efforts to contain the virus. Anon (2020) noted that the COVID-19 outbreak had severely affected health systems, economies, and governments around the world. These effects compelled several governments to implement immediate measures and restrictions to contain the virus's spread. One widely recommended measure to curb the spread was the imposition of travel restrictions (Ma, Rogers, & Zhou, 2020; Salisu, Ebuh, & Usman, 2020).

Tigerstrom and Kumanan (2020) reported that travel restrictions are part of an extensive strategy to minimise community transmission of infectious diseases during pandemic times. Notably, Pattani (2015) suggested travel restrictions as a strategy adopted to suppress the 2014-2016 Ebola virus outbreaks. Travel restrictions are designed to interrupt the transmission cycle, especially because the virus is airborne and spreads through human-to-human contact (Wu et al., 2020). The economic effects of travel restrictions during a pandemic are said to be damaging, however. Studies (Altig et al., 2020; Vrkljan & Hendija, 2016; Zaremba et al., 2021) have shown that restrictive measures implemented by many countries affected businesses, job security, and essential services. The imposition of travel restrictions, in particular, compounds the effects of the pandemic by undermining social interactions and exchanges. Since economic activity relies on such interactions, the restrictive travel measures adversely affect markets and countries worldwide.

People move from one location to another to exchange social and material resources (Moyle, Croy and Weiler, 2010). Such movements are central to human interaction and result in a variety of outcomes (Teichman & Foa, 1975). The Social Exchange Theory (SET) provides an understanding of the complex web of human interactions and exchange of social and material resources through movements. The SET premise is that, to sustain interaction, at least an exchange of resources between individual actors or groups must be present (Ap, 1992). In this context, travelling, migration, and tourism occur as forms of resource exchange. A direct implication of the SET is that any attempt to restrict travel will reduce global oil demand, particularly for transportation fuel, as airlines cut flights due to cancellations of business trips and holidays. Another underlying intuition of the SET is the assumption that oil is an important input for the production process of most firms. Therefore, its price is more likely to affect the general price level of goods and services, leading to changes in total costs and earnings.

The arguments set forth by the SET suggest that restricting movements would not be in the interests of individuals and countries at large, as it has the propensity to disrupt the economic and social structures of society (Pearce, 1995; Nash, 1989; Santos & Profit, 2004). Indeed, the declaration of the COVID-19 pandemic heightened economic anxieties and uncertainties globally and weakened economic sentiment among the population. Aloui, Aissa, and Nguyen (2011) also noted that countries are susceptible to changes in commodity prices during pandemics. A similar study by Sharif, Aloui, and Yarovaya (2020) reported that, two months after the onset of the COVID-19 epidemic in Wuhan City, oil prices fell by around 30%, the largest slump since the Gulf War.

Recent evidence reveals that from January to June 2020, global crude oil prices declined by nearly 66%, with West Texas Intermediate briefly entering negative territory, while petroleum prices in various Sub-Saharan African economies decreased by approximately 30% (Mwape et al., 2024). These price drops were attributable to shocks partly triggered by the fears over the dramatic news of infections and patient death cases coming from different parts of Europe. Attempts to stabilise the oil market by the end of mid-year 2020 through demand and production cuts proved ineffective as the pandemic persisted (Schneider & Domonoske, 2020).

The current global economic effects of the pandemic are uncertain, given the volatile swings of oil prices (Organisation of the Petroleum Exporting Countries [OPEC], 2023). Gormsen and Koijen (2020) find evidence that the effects on oil prices are persistent, suggesting that the impact might not be transitory. Salisu, Ebuh, and Usman (2020) also found that the pandemic period had greater initial and long-run effects of both own and cross shocks on oil prices relative to the pre-pandemic period, using a panel Vector Autoregressive (pVAR) model. Correspondingly, other research (Baker et al., 2020; Goodell & Huynh, 2020; Zhang et al., 2020) corroborated the observation that the COVID-19 pandemic heightened volatility in commodity prices. Other researchers (Goodell, 2020; Ozili & Arun, 2020) predicted a greater long-term impact. Furthermore, recent post-pandemic evidence suggests that structural transmission mechanisms of oil-dependent and developing economies were significantly altered following COVID-19 disruptions, thus indicating that fuel price dynamics post-2020 may not merely follow pre-pandemic trends (Mili & Houari, 2025).

The situation is not different in many African countries, including Ghana. Dickson and Yao (2020) noted that pandemic-related restrictions resulted in immense economic losses for several African countries. They found that the reduction in economic activities, such as tourism, export sales, and supply chain instability, resulted in the decline of Gross Domestic Product (GDP) growth in Ethiopia from 6.2% to 3.2%; 3.5% to 1.85% in Uganda, and 3.3% to 2% in Tanzania by the end of 2020. In Ghana, studies like Danquah and Schotte (2020) and Kyei et al. (2023) contend that the pandemic-induced restrictions on people's movement and the closure of Ghana’s borders led to food supply shortages that contributed to a general rise in inflation. Other existing studies (Issahaku & Abu, 2020;

Asante & Mills, 2020) largely focused on the impact of COVID-19 restrictions on macroeconomic variables.

Although the global oil market during the COVID-19 pandemic has been extensively studied, limited empirical work has been conducted on how mobility restrictions during the pandemic affected the domestic fuel dynamics in sub-Saharan Africa, particularly Ghana (Chikobvu & Makoni, 2026). This study adds to the scarce literature on the structural implications of COVID-19 on fuel price behaviour. In this paper, an intervention time series framework is used to investigate whether the COVID-19 induced mobility disruptions triggered a structural shift in the fuel price dynamics in Ghana. The primary objective of the study is to examine the hypothesis that fuel prices after COVID-19 intervention measures (travel restrictions) are not significantly different from fuel prices before the relaxation of intervention measures.

In particular, the analysis follows a Box–Tiao (1975) intervention analysis in an ARIMA framework, where the pre-intervention period (January 2016–December 2020) sets the counterfactual stochastic structure of fuel prices, and January 2021 is considered as the structural intervention point for the shift from pandemic-related stabilisation measures to a post-restriction adjustment regime. The causal effect is identified as the systematic difference between actual fuel prices post-2021 and the counterfactual trajectory predicted by the pre-intervention ARIMA model. This methodology ensures that the extended sample period (2016–2023) is used not to attribute all fluctuations to COVID-19, but to establish the essential baseline needed for the reliable identification of structural breaks linked to mobility disruptions caused by the pandemic.

The motivation for this research is the dearth of empirical evidence on the effect of pandemic-induced restrictions on mobility on local fuel markets in Ghana. While global studies have documented changes in oil prices during the pandemic, it is unclear how much these disruptions have led to structural changes in Ghana’s domestic fuel pricing systems. The work offers three significant additions to the existing literature. First, it provides empirical evidence on the structural effects of COVID-19 mobility disruptions on the fuel price behaviour in Ghana. Second, it emphasises the usefulness of intervention time-series modelling in identifying structural shifts due to external shocks in the emerging energy markets. Third, the study offers policy-relevant insights on the impact of mobility constraints and their relaxation on the dynamics of domestic fuel pricing. The following sections include a literature review, research methodology, empirical results, policy implications of findings and concluding remarks.

Literature Review

The effects of the COVID-19 pandemic on energy markets, fuel demand, and price volatility have been the subject of numerous research studies. Understanding these dynamics requires both a solid theoretical foundation and robust empirical analysis. In this sense, the relationship between mobility restriction and fuel demand can be interpreted through well-known theoretical frameworks. In parallel, time-series modelling approaches have been extensively used for capturing the fluctuations in fuel prices during economic disruption periods.

Social Exchange Theory (SET) is employed as a theoretical foundation to explore the association between fuel demand and mobility restrictions. SET suggests that economic and social interactions happen via the exchange of resources between people and communities (Ap, 1992). Mobility is a prerequisite for these exchanges, facilitating transportation, tourism and other economic activities that are very fuel dependent. Thus, restrictions on movement during pandemics disrupt these exchanges and may affect fuel demand patterns and pricing behaviour. In this context, the restrictions of mobility during the pandemic could have contributed to the decrease in fuel consumption related to the transportation during the first phases of the pandemic. The easing of the restrictions could have caused changes in the fuel demand and price mechanisms. Thus, the use of SET provides a theoretical basis to understand how disruptions in human mobility convert into tangible changes in the behaviour of the fuel market.

Despite SET's applicability, the theory has been criticised for being overly dependent on rational, stable exchange relationships, which may not sufficiently explain abrupt, externally forced disruptions, such as pandemics (Cropanzano et al., 2017). In particular, the theory does not explicitly consider large-scale exogenous shocks that simultaneously affect supply and demand conditions. This limitation is crucial in the COVID-19 setting because mobility constraints imposed by governments, as opposed to private exchange decisions, drastically altered economic activity. This study contributes to filling this gap by empirically investigating if such exogenous shocks resulted in an observable structural change in fuel price dynamics, and thus extends the application of SET to a crisis context.

The challenge often encountered in analysing time series data is the dataset's non-stationarity caused by significant fluctuations during events such as the COVID-19 pandemic. Consequently, researchers explore statistical models for analysing random time series and assess their impacts. A cursory study of the literature reveals a plethora of statistical approaches for analysing non-stationary data, including Difference-in-Differences (DID), Fractional Integration Techniques, Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models, and linear and non-linear models, as demonstrated in empirical studies such as Fu and Shen (2020), Gil-Alana and Monge (2020), Salisu and Adediran (2020), Huang and Zheng (2020), and Ertugrul et al. (2020).

The literature addressing COVID-19 and the energy sector uniformly characterises the pandemic as a major exogenous shock with widespread consequences for both firm performance and market dynamics. At the firm level, evidence indicates that firms in heavily affected areas experienced significant performance declines, mainly because of disruptions in productivity and decreases in revenues (Fu and Shen, 2020). The decrease in performance indicates that the pandemic restrictions not only limited operational activities, but also had a negative impact on the financial resilience of companies in the energy sector.

Empirical evidence indicates that COVID-19 has increased uncertainty and volatility in energy prices at the market level. Different studies, using different methodological approaches, found that the uncertainty caused by the pandemic had a significant impact on energy market behaviour. For example, using a fractional integration approach, Gil-Alana and Monge (2020) found that the oil price shocks during the pandemic were mostly transitory, but some persistence was observed. Salisu and Adediran (2020) find that pandemic and epidemic uncertainties significantly increased energy market volatility in their bivariate predictive model. Likewise, Huang and Zheng (2020) emphasise the use of investor sentiment in crude oil price movement during the pandemic. Combined, these results suggest that both fundamental economic disruptions and behavioural responses contributed to the increased instability in energy markets during the crisis period.

Additional evidence from country-specific and sectoral studies further supports the volatility and uncertainty effects of the pandemic. Using a GARCH model, Ertugrul et al. (2020) found that the diesel price volatility in Turkey was highest during the time of strict government restrictions (curfews, travel bans, etc), which indicates sharp adjustments in consumption patterns. In a related context, Boldea and Boldea (2021) found that the COVID-19 restrictions had a significant effect on the inflation dynamics in Southern and Eastern Europe, with oil price fluctuations having a greater effect on less economically resilient countries.

Early in the pandemic, studies on volatility were conducted, while recent studies point to structural changes in oil-dependent economies driven by COVID-19. Mili & Houari (2025) shows that the transmission mechanisms after the pandemic are substantially different from the pre-pandemic dynamics, indicating that the conventional linear models might be insufficient to capture the regime changes associated with pandemic disruptions. Similarly, Mwape et al. (2024) document large declines in global and regional oil prices, including the historic collapse in West Texas Intermediate prices and large declines in petroleum prices in Sub-Saharan Africa, again highlighting the demand-driven nature of the shock. Moreover, Hameed et al. (2024) note that oil price shocks in the COVID-19 period exhibited asymmetric and non-linear transmission patterns, suggesting that pandemic-induced disruptions are fundamentally distinct from typical supply-side shocks.

The literature provides three main lessons: (i) COVID-19 had a negative impact on the performance of firms through disruptions to production and revenues; (ii) the pandemic increased the uncertainty and volatility of the energy markets through economic and behavioural channels; (iii) the pandemic resulted in structural and non-linear changes in price dynamics that are difficult to model using traditional approaches. However, little attention has been paid to how such pandemic-induced shocks are manifested in developing and fuel-dependent economies such as Ghana, where institutional and market conditions may further shape price dynamics despite these advances.

The present study seeks to investigate the impact of the COVID-19 pandemic on fuel prices in Ghana. The study examines how the mean level of a series changes after an intervention (travel restrictions), assuming the same ARIMA structure holds for the series both before and after the intervention. By focusing on an intervention-based time-series framework, the study contributes to the literature by providing context-specific evidence on how pandemic-induced shocks influence fuel price behaviour in a developing economy.

Methods

A time-series study design was employed to examine the effect of COVID-19 restrictions on fuel prices in Ghana. According to Cochrane (1997), a time series is a sequential set of data points measured over successive time points. This study design was preferred because it enabled us to examine the behaviour of historical fuel prices and to develop an appropriate model that describes the inherent structure of fuel price changes. Monthly gasoline prices were sourced from the Bank of

Ghana commodity database. The data were obtained manually from the official online database of the Bank of Ghana and cross-checked for consistency across reporting periods to ensure accuracy and completeness (Bank of Ghana, 2023). The data cover January 2016 to April 2023. The longer sample period allows the pre-pandemic period observations (2016–2020) to capture the underlying dynamics of fuel prices prior to COVID-19 disruptions. These observations provide an important baseline to develop a counterfactual path to assess post-intervention behaviour of prices.

The dataset was subjected to data cleaning and validation prior to analysis. Missing observations were evaluated by looking at breaks in the time series of monthly observations and by creating summary statistics to identify null or undefined values. In the examination of outliers, both graphical and statistical methods were used to identify observations that deviated markedly from the overall distribution, including time-series plots and standardised z-scores. Furthermore, consistency checks were carried out through visual inspection of the series for erratic patterns and through cross-validation of the recorded values with the official source database.

Model formulation

Suppose that at time $t = T$ (where T will be known), there has been an intervention in a time series. We defined intervention as a change to a procedure, law, or policy, etc., that is intended to change the values of the series x_t. Subsequently, an intervention analysis was performed on the series x_t. According to Box and Tiao (1975), intervention analysis in time series refers to the analysis of how the mean level of a series changes after an intervention, assuming that the same ARIMA structure holds for the series both before and after the intervention. The approach has seen some useful applications in areas such as the investigation and forecast of economic factors (Chung et al., 2008), tourism forecasting (Cho, 2001) and system scheduling and simulation (Ip et al., 1999).

The estimation procedure is split into pre- and post-intervention periods to identify the structural effect associated with COVID-19 related disruptions in mobility in a reliable manner. The ARIMA model is estimated using the pre-intervention period (January 2016–December 2020) to show the underlying trend, persistence, and autocorrelation structure of fuel prices before the policy changes related to the pandemic. The intervention point is January 2021, when the government-enforced stabilisation and subsidy measures of 2020 were replaced by a post-restriction market-adjustment framework.

The ARIMA model's out-of-sample forecasts prior to the intervention demonstrate the counterfactual path of fuel prices in the absence of structural breaks induced by the pandemic. The intervention effect is the systematic difference between the observed fuel prices after 2021 and the corresponding counterfactual forecast. The presence of a statistically significant deviation provides evidence of a structural break in the mean level of the fuel price series related to the COVID-19 intervention. It is important that we employ data prior to 2021 to set the identification benchmark, and not assume that the entire sample period is pandemic-driven.

Drawing from insights gained from previous studies, we construct the ARIMA (p, d, q) model, devoid of intervention, as follows:

$$x'_t = \phi_1 x'_{t-1} + ... + \phi_p x'_{t-p} + \theta_1 w_{t-1} + ... + \theta_q w_{t-q} + w_t, \quad \text{......................................(1)}$$

where $x'_t = x_t - x_{t-1}$ is the differenced series (could be differenced more than once), the error term $w_t \overset{iid}{\sim} N(0,\ \sigma_w^2)$ and

p = order of the autoregressive part;

d = degree of first differencing involved;

q = order of the moving average part.

Equation (1) is restated as:

$$\Phi(B)(1-B)^d x_t = \Theta(B) w_t,$$

$$x_t = (1-B)^{-d}\Phi^{-1}(B)\Theta(B)w_t, \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

where B is the backshift operator and $\Phi(B) = 1 - \phi_1 B - \cdots - \phi_p B^p$ is an AR polynomial; $\Theta(B)$ is an MA polynomial, where $\Theta(B) = (1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q)$.

Now, let z_t = the amount of change at time t that is attributable to the intervention. By definition, $z_t = 0$ before time T (time of the intervention). The value of z_t may or may not be 0 after time T. Consequently, the overall model, including the intervention effect, according to Box and Tiao (1975), may be written as:

$$y_t = z_t + x_t. \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

Estimating the Intervention Effect

The study proceeded further to demonstrate how the intervention effect was estimated and considered the simple model

$$y_t = \delta_0 I_t + x_t, \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

where I_t is an indicator variable such that $I_t = 1$ when $t \geq T$ and $I_t = 0$ when $t < T$, and $x_t = (1-B)^{-d}\Phi^{-1}(B)\Theta(B)w_t$. Given the information about I_t, we rewrite Equation (4) formally, as

$$\pi(B)y_t = \delta_0 \pi(B) I_t + w_t, \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

where $\pi(B) = (1-B)^d \Phi(B)\Theta^{-1}(B) = 1 - \sum_{i=1}^{\infty} \pi_i B^i$. Letting $a_t = \pi(B) I_t$ and $b_i = \pi(B) y_t$, we can write Equation (5) in the form of a simple linear model as: $b_i = \delta_0 a_t + w_t, i = 1, 2, \ldots, n.$ …………… (6)

Subsequently, the parameter δ_0 of Equation (6) was obtained through the method of maximum likelihood estimation with an estimator of δ_0 approximately given as:

$$\hat{\delta}_0 = \frac{\sum_{i=1}^{n} a_t b_t}{\sum_{t=1}^{n} a_t^2}$$

with $var(\hat{\delta}_0) = \frac{\sigma_w^2}{\sum_{t=1}^{n} a_t^2}$.

Analysis

The analysis begins by studying the time series of fuel prices in an effort to detect patterns, trends and possible structural changes connected with the COVID-19 intervention. The time series plot shows the variation of fuel price with clear variation during the intervention period. Prior to model estimation, it is necessary to ensure that the time series satisfies the stationarity requirement of ARIMA modelling. A time series that is not stationary may yield incorrect parameter estimates and lead to incorrect conclusions. Stationarity is evaluated by visually inspecting the time series plot and analysing autocorrelation patterns. If the original fuel price series demonstrates non-stationary behaviour, differencing is used to eliminate trends and stabilise the series' mean. The differenced series is then evaluated to confirm that stationarity has been achieved before proceeding with model identification.

The appropriate ARIMA model was identified using autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. These plots provided guidance on the model's autoregressive (AR) and moving-average (MA) components. Model selection was further refined using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), and the model with the lowest information criterion was selected for estimation. Model parameters were estimated using maximum likelihood estimation, and the resulting ARIMA model served as the foundational representation of fuel price behaviour.

The study incorporated an intervention variable in the ARIMA model to quantify the impact of the COVID-19 travel restrictions. We examined the intervention coefficient to determine if the implementation of the travel restrictions caused a statistically significant change in fuel prices. If the intervention coefficient is statistically significant, then the intervention affected the fuel price dynamics. If the intervention coefficient is not significant, then there was no structural change.

Finally, diagnostic evaluations were performed to evaluate model adequacy. Residual analysis was performed to verify that the residuals exhibited white noise, indicating that the model accurately captured the underlying structure of the fuel price time series.

Findings

Table 1 presents the monthly mean petrol prices as the main series for the analysis. Data prior to the intervention point (January 2021) were used to estimate the ARIMA model for the pre-intervention series. The choice of January 2021 as the intervention point was based on the government's response to the first recorded COVID-19 cases in Ghana on March 12, 2020. The government introduced subsidy programs for electricity, water, and fuel to mitigate the impact of the COVID-19 pandemic until the last quarter of 2020. Any forecasts made after January 2021 are out-of-sample predictions.

Table 1: Indicative Petrol Price

	Monthly Average											
Year	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
2023	14.12	14.06	13.20	12.95								
2022	6.68	7.55	9.05	9.30	9.47	10.62	11.27	10.88	11.13	12.29	17.43	16.58
2021	4.91	5.03	5.25	5.32	5.91	6.00	6.11	6.12	6.18	6.49	6.79	6.66
2020	5.39	5.40	5.14	4.09	4.03	4.40	4.68	4.71	4.66	4.59	4.58	4.64
2019	4.89	4.90	5.15	5.19	5.20	5.16	5.15	5.15	5.24	5.30	5.32	5.34
2018	4.56	4.57	4.49	4.54	4.60	4.85	4.83	4.72	4.98	5.12	5.11	4.94
2017	4.03	4.10	4.21	4.01	3.88	3.82	3.74	3.78	4.20	4.28	4.34	4.46
2016	3.46	3.32	3.33	3.42	3.53	3.61	3.49	3.50	3.62	3.66	3.58	3.63

Before determining the ARIMA model for the pre-intervention series, the series was tested for stationarity using a unit root test. The ADF test yielded a p-value of 0.9101; therefore, the null hypothesis of a unit root could not be rejected, indicating that the pre-intervention series was non-stationary. After first differencing, the ADF test produced a p-value of 0.01; therefore, the null hypothesis was rejected, indicating that the differenced series was stationary. Given the need for one differencing operation, the *d* value for our ARIMA (*p, d, q*) model was determined to be 1 (Jenkins, 1970).

This finding suggests that petrol prices were generally stable before the relaxation of travel restrictions, with a pre-intervention price averaging GH¢ 4.99 per litre (2016-2020). Ghazanfari (2020) explains that during pandemics, national lockdown policies in most countries reduce residents' income and, therefore, their expenditures. This phenomenon reduces routine activities, such as entertainment, outdoor gatherings, dining and shopping, thereby sharply decreasing the demand for automobile fuel. Similar views were shared by Ertugrul et al. (2020) and Fu and Shen (2020). The authors found that, prior to the removal of the pandemic-related restrictions, productivity was severely affected, revenues dropped, and consumption declined. These findings were at variance with the social exchange theory, which prescribes free interaction among humans leading to a range of outcomes (Teichman & Foa, 1975).

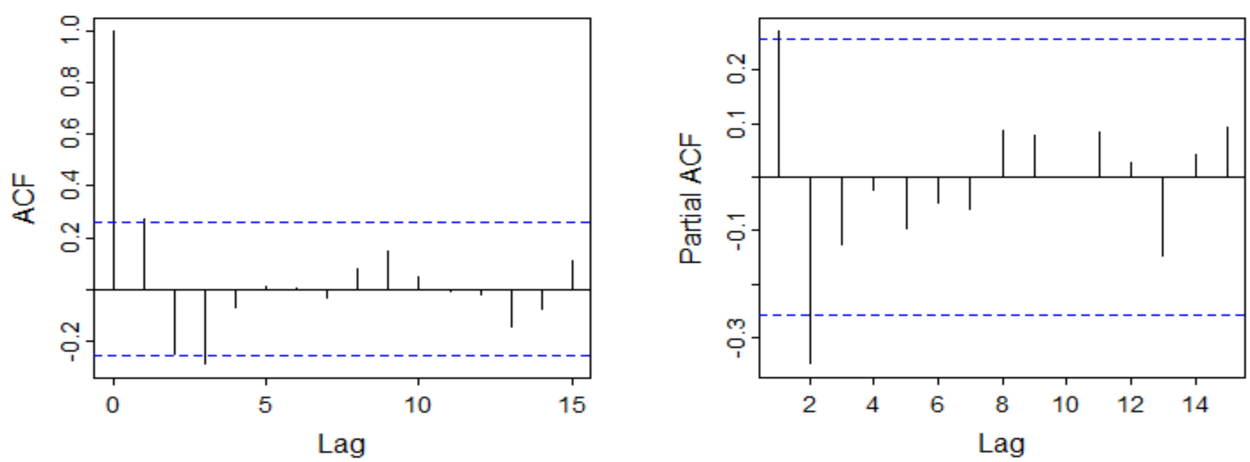

Figure 1: ACF and PACF of the first-order difference of the pre-intervention series

Further, the Ljung and Box (1978) test was conducted to examine whether the projected model follows a white noise process. Figure 1 shows the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of the first-order difference of the series. The PACF shows that the first two lags are significant; hence, we may select $p = 2$ and $d = 1$ for our ARIMA (p, d, q) model. Table 2 shows a comparative analysis of the ARIMA models: ARIMA (2, 1, 0), ARIMA (2, 1, 1) and ARIMA (2, 1, 2).

Table 2: Comparative analysis of ARIMA(2, 1, 0), ARIMA(2, 1, 1) and ARIMA(2, 1, 2)

	ARIMA(2, 1, 0)			ARIMA(2, 1, 1)			ARIMA(2, 1, 2)		
	Estimate	**SE**	**p-value**	**Estimate**	**SE**	**p-value**	**Estimate**	**SE**	**p-value**
AR(1)	0.3636	0.1224	0.0044	0.7219	0.2962	0.0181	0.7155	0.2722	0.0112
AR(2)	–0.3392	0.1207	0.0069	–0.4312	0.1190	0.0006	–0.3896	0.2285	0.0941
MA(1)				–0.4180	0.3323	0.2139	–0.4073	0.2952	0.1734
MA(2)							-0.054	0.2437	0.8254
Constant	0.0225	0.0236	0.3446	0.0225	0.0189	0.2409	0.0224	0.0185	0.2301
AIC		–0.5078			–0.4929			–0.4592	
BIC		–0.3657			–0.3152			–0.2461	

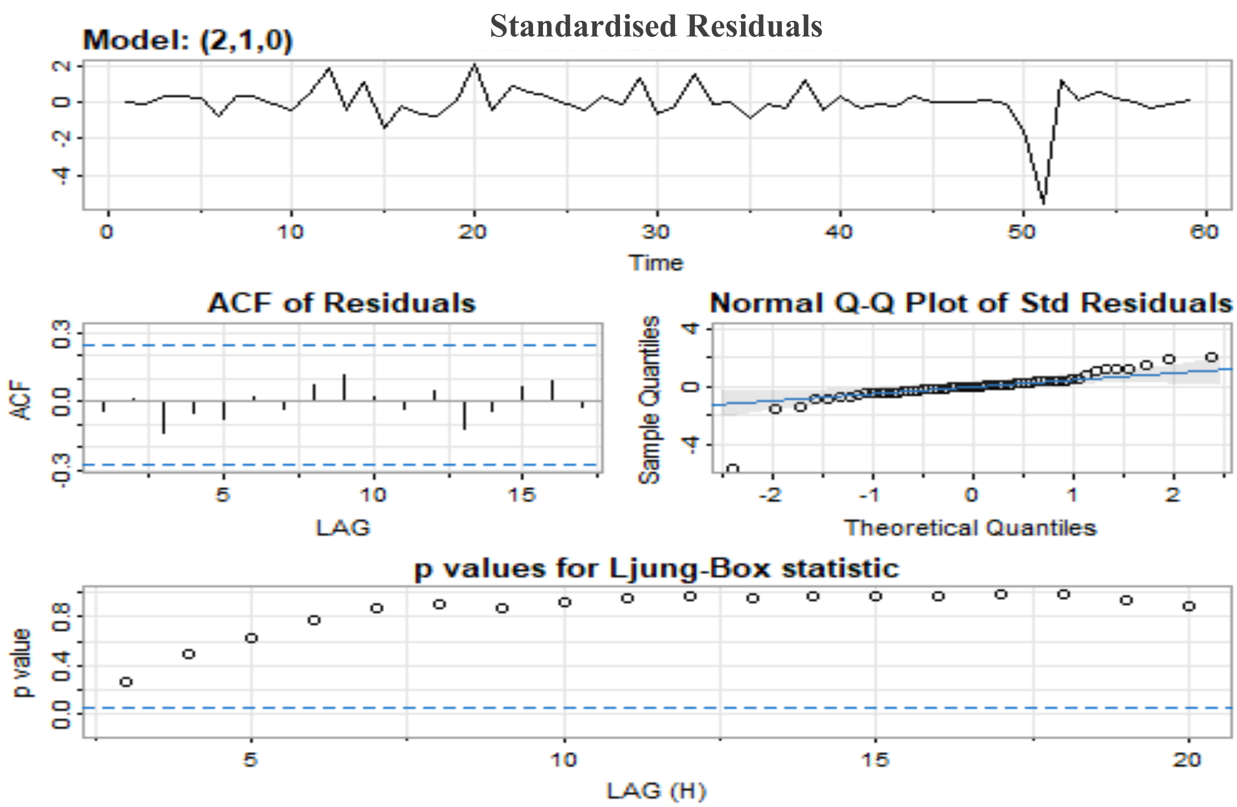

Figure 2: Standardised Residual, ACF of Residual, Normal Q-Q of Standard Residuals, and p-values of Ljung-Box Statistic

The p-values for the MA (1) and MA (2) terms in ARIMA (2, 1, 1) and ARIMA (2, 1, 2), respectively, are greater than 0.05 and are therefore not significant. Moreover, the AIC and BIC of ARIMA (2, 1, 0) are smaller compared with those of ARIMA (2, 1, 1) and ARIMA(2, 1, 2). Thus, the optimal model is ARIMA (2, 1, 0).

From Figure 2, the plot of the standardised residuals shows no trend and, in general, no changing variance over time. The ACF of the residuals shows no significant autocorrelations. In the Q-Q plot, the data points appear to align along a straight line, indicating that the residuals follow a normal distribution. The p-values for the Ljung-Box-Pierce statistics, for each lag up to 20, surpass 0.05, affirming the retention of the null hypothesis of independence in the residuals. These statistical measures validate the robustness of our optimal model, ARIMA (2, 1, 0).

Moving forward, we used the ARIMA (2, 1, 0) model to forecast values for the period after the intervention and subsequently calculated the differences between actual and predicted values. Table 3 shows the observed and the forecast values for the period after the intervention.

Table 3: The forecasted and observed values after the intervention

Month-year	Observed	Predicted	Difference
Feb-21	5.03	4.71	0.32
Mar-21	5.25	4.72	0.53
Apr-21	5.32	4.74	0.58
May-21	5.91	4.76	1.15
Jun-21	6.00	4.79	1.21
Jul-21	6.11	4.81	1.30
Aug-21	6.12	4.83	1.29
Sep-21	6.18	4.85	1.33
Oct-21	6.49	4.88	1.61
Nov-21	6.79	4.90	1.89
Dec-21	6.66	4.92	1.74
Jan-22	6.68	4.95	1.73
Feb-22	7.55	4.97	2.58
Mar-22	9.05	4.99	4.06
Apr-22	9.30	5.01	4.29
May-22	9.47	5.04	4.43

Jun-22	10.62	5.06	5.56
Jul-22	11.27	5.08	6.19
Aug-22	10.88	5.10	5.78
Sep-22	11.13	5.13	6.00
Oct-22	12.29	5.15	7.14
Nov-22	17.43	5.17	12.26
Dec-22	16.58	5.19	11.39
Jan-23	14.12	5.22	8.90
Feb-23	14.06	5.24	8.82
Mar-23	13.20	5.26	7.94
Apr-23	12.95	5.28	7.67
Total	**252.44**	**134.75**	**117.69**
Mean	**9.35**	**4.99**	**4.36**

The post-intervention period (2021-2023) was characterised by highly volatile petrol prices. These prices ranged from a monthly average of GH¢ 5.03 per litre in February 2021 to about GH¢ 12.95 per litre by the end of April 2023. The sharp rise in petrol prices led to a post-intervention monthly average of GH¢ 9.35 per litre. These erratic price hikes were partly attributed to uncertainties surrounding the pandemic (Salisu & Adediran, 2020) and investor sentiment (Huang & Zheng, 2020). Similar studies (Baker et al., 2020; Goodell & Huynh, 2020; Zhang et al., 2020) also reported that COVID-19 was responsible for the volatility in fuel prices during the post-intervention period. Goodell (2020) and Ozili and Arun (2020) predicted a greater long term impact.

To assess the intervention's effect, the normality of the differences between actual values after the intervention and forecasted values was first tested. The Shapiro-Wilk test produced a p-value of 0.012. At the 5% level, this suggests mild deviation from normality; however, at the 1% level, the null hypothesis of normality cannot be rejected. Thereafter, a paired-samples t-test was used, with a test statistic of 6.481 and a $p < 0.001$, to conclude that the observed and forecasted values of the series differ significantly after the intervention.

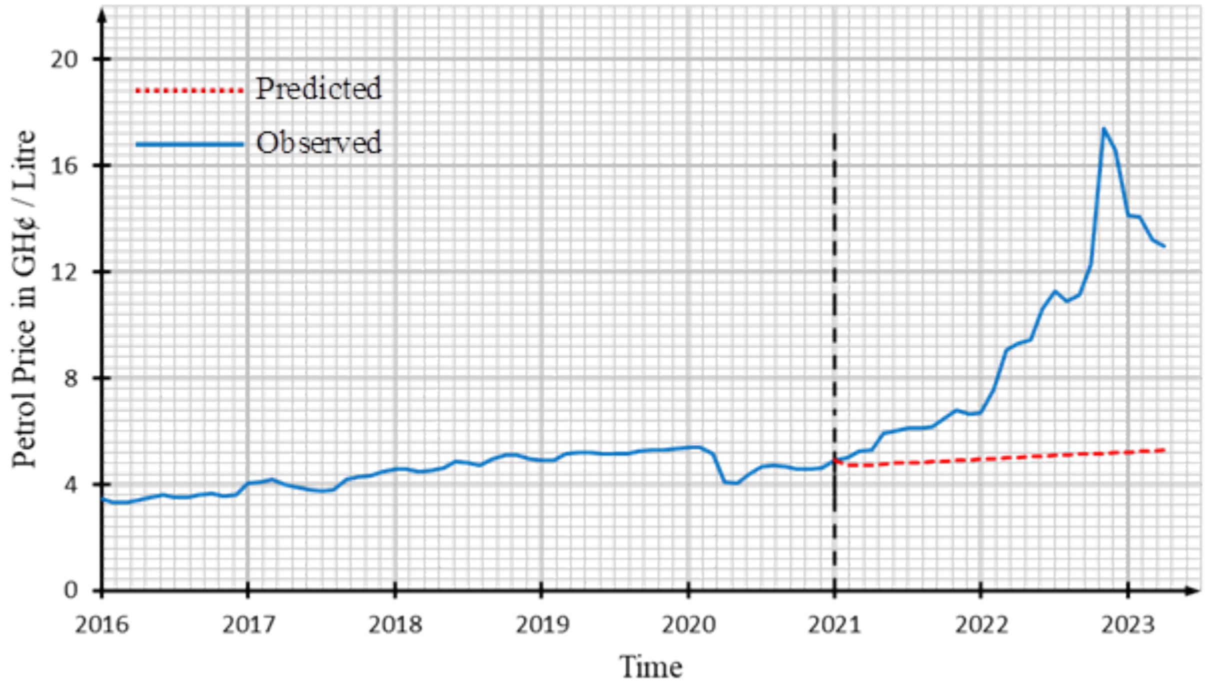

Figure 3: The observed time series graph together with that of the forecasted values after the intervention

This result indicates a significant difference between the monthly average petrol series before and after the relaxation of COVID-19 restriction measures. The difference between the predicted and observed responses during the post-intervention period yielded a semi-parametric Bayesian posterior distribution for the causal effect, as depicted in Figure 3.

It is important to note that during the post-intervention period, the response variable (mean monthly petrol prices) had an average value of approximately GH¢ 9.35 per litre. In contrast, in the absence of an intervention, the expected average response would have been GH¢ 4.99 per litre, with a 95% confidence interval of [4.72, 5.26]. Subtracting the predicted values from the observed values yields an estimated causal effect of GH¢ 4.36 per litre, with a 95% confidence interval of [4.09, 4.63]. Alternatively, when the individual data points during the post-intervention period are summed up, the response variable would have an overall value of GH¢ 252.44 per litre (see Figure 3). In contrast, without the intervention, an expected sum would have been GH¢ 134.75 per litre, with a 95% confidence interval of [127.26, 142.24]. In relative terms, the response variable increased by 87%.

The 95% interval for this percentage is [74%, 100%]. This result shows that the positive effect observed during the intervention period is statistically significant and unlikely to be due to random fluctuations. The probability of obtaining this effect by chance is very small (Bayesian one-sided tail-area probability $p = 0.001$). Hence, the causal effect is statistically significant.

Discussion of Results

This study is based on Social Exchange Theory (SET), which suggests that economic and social relationships are sustained through the exchange of resources enabled by human mobility and interaction. In this theoretical setting, mobility constraints are assumed to hinder the economic exchange processes, especially in sectors highly reliant on transportation and energy consumption. The relaxation of such restrictions is expected to increase mobility and hence increase demand and influence trends in the market. The results of the analysis show a statistically significant structural break in the fuel price behaviour in Ghana after the lifting of the COVID-19 mobility restrictions, which is consistent with theoretical assumptions.

The results show that the fuel costs in the post-intervention era diverged systematically from the path projected by pre-pandemic trends. This shift indicates a structural break in the fuel price series, implying that the price behaviour after 2021 cannot be fully explained by past stochastic patterns alone. The magnitude and duration of this deviation provide strong evidence that the COVID-19 related mobility disruptions and their subsequent easing had a significant impact on the underlying dynamics of fuel pricing in Ghana. This result confirms that fuel prices responded to policy interventions affecting mobility and transportation demand.

From a theoretical point of view, these findings expand the application of SET to a crisis context with exogenous shocks. Traditionally, SET presupposes voluntary and stable exchange relationships (Moyle, Croy & Weiler, 2010), but the COVID-19 pandemic imposed external mobility constraints that interrupted these interactions. The change in the structure of fuel prices is a consequence of the disruption and the reorganisation of economic exchange processes after the introduction and the cancellation of travel restrictions. Such a shift shows that the theory is still applicable even when the exchanges are constrained by external factors, making it more useful in explaining the economic dynamics in times of systemic disruption.

The empirical results of the study are consistent with previous studies that have reported the effects of COVID-19 on energy markets. Previous studies have shown that the pandemic-induced mobility restrictions and economic slowdowns have disrupted fuel demand and led to greater volatility in oil prices (Salisu & Adediran, 2020; Huang & Zheng, 2020). These disruptions are also supported by the broader global evidence as the main drivers of the energy price volatility during the pandemic (Baker et al., 2020; Goodell & Huynh, 2020; Zhang et al., 2020). Previous studies have focused on short-term volatility and immediate market reactions, but the present study adds to the literature by showing a persistent structural change in fuel price behaviour and thereby capturing longer-term dynamics in a developing economy context.

Moreover, recent studies since the pandemic indicate that COVID-19 has triggered more profound structural adjustments in energy markets, particularly in oil-dependent and developing economies (Mwape et al., 2024; Mili & Houari, 2025; Hameed et al., 2024). The results of this study contribute to this growing body of evidence by showing that fuel price dynamics in Ghana have undergone a regime shift rather than merely a temporary fluctuation. This highlights the need to consider long-term structural effects when evaluating the economic consequences of global shocks like pandemics.

The study shows that intervention analysis in an ARIMA context is a useful tool to detect structural changes in time-series data from a methodological perspective. The approach allows researchers to distinguish between the normal time-series behaviour and statistically significant deviations caused by external shocks by constructing a counterfactual trajectory based on pre-intervention dynamics.

This strengthens the causal inference and provides a solid basis for evaluating the economic impact of policy interventions.

The results also have important policy implications. The sharp increase in fuel prices following the easing of mobility restrictions indicates that fuel markets are very sensitive to changes in transportation demand and economic activity. Since fuel plays a key role in transportation costs, inflation, and the overall economy, the impacts of policies that influence mobility should be examined in terms of their wider economic impacts. Specifically, the results underscore the importance of coordinated policy interventions that consider the possible spillover effects of public health measures on energy markets and economic stability.

Conclusion

This paper examines the effect of COVID-19 related mobility disruptions on fuel price behaviour in Ghana using an intervention time-series approach within an ARIMA framework. Specifically, the study examined the hypothesis that fuel prices following the relaxation of COVID-19 mobility restrictions do not significantly differ from pre-intervention levels. The empirical results reject this hypothesis and provide strong evidence of a statistically significant structural break in the fuel price behaviour after the intervention period.

Using pre-intervention dynamics from 2016 to 2020, the study generated a counterfactual trajectory and showed that fuel prices consistently deviated from the predicted path from 2021 onwards. The approximately 87% relative increase and the estimated average causal effect of GH¢4.36 per litre suggest that the observed changes are not due to random fluctuations but rather a sustained change in the underlying dynamics of fuel prices. This implies that historical stochastic patterns are not sufficient to explain fuel price behaviour in the post-pandemic period.

In summary, the findings extend the focus beyond short-term volatility and immediate COVID-19-related market disruptions, adding to the existing literature. Previous studies have mostly documented transitory demand shocks and price fluctuations in global energy markets. This study provides evidence of a persistent structural change in fuel price dynamics in the setting of a developing economy. This points to an important departure from previous findings by showing that pandemic-related disruptions can cause long-term regime changes rather than just transitory effects.

The results have theoretical implications supporting and extending the importance of SET for understanding economic behaviour under situations of restricted mobility. The findings suggest that disruptions in mobility have a significant effect on economic exchange processes, and that the relaxation of such constraints results in a reconfiguration of demand dynamics, especially in petrol markets. This points to the significance of mobility in shaping energy consumption patterns and price behaviour.

In practical terms, the findings indicate that fuel markets are highly responsive to policy interventions that affect transportation and economic activity. Given the importance of gasoline prices in determining transportation costs, inflation, and overall economic stability, policymakers should carefully evaluate the larger economic consequences of mobility-related initiatives. The findings emphasise the need to incorporate energy market responses into the design and implementation of public health and mobility strategies, especially in developing countries.

Implications: Theoretical and Policy Implications

This study contributes to the theoretical literature by extending the application of the Social Exchange Theory to fuel price dynamics under external policy intervention. Results suggest that the effects of mobility disruptions, such as COVID-19 travel restrictions, can be substantial for economic exchange processes and, consequently, commodity price behaviour. This supports the theoretical proposition that economic interactions, particularly in transportation and mobility, are significant drivers of fuel demand and prices.

In addition, the study also contributes methodologically by demonstrating the usefulness of the intervention analysis within the ARIMA framework to detect structural breaks in economic time series. The study employs intervention analysis to assess the impact of travel restrictions due to COVID-19. The study offers empirical support for the use of time series intervention models for evaluating causal impacts of external shocks and policy interventions.

This research has significant policy and regulatory ramifications. Travel restrictions profoundly influence fuel prices, suggesting that mobility-related policy measures can yield economic repercussions beyond public health objectives. Policymakers should consider the impact of mobility restrictions on fuel markets when designing and implementing public health interventions. The results emphasise the importance of closely monitoring fuel price behaviour during major policy interventions or external shocks for energy regulators and fuel pricing authorities. Understanding how fuel prices respond to changes in mobility can help policymakers set fair prices and avoid unintended economic effects. These findings are of interest to transportation planners and economic policymakers because fluctuations in fuel prices influence transportation costs, inflation and economic stability. Forecasting the response of fuel prices to mobility restrictions can help to better plan policy and manage the economy during crises.

Limitations and Future Research Directions

Intervention analysis regards the onset of COVID-19 travel restrictions as one structural event, while the pandemic is composed of several changing policy measures. The overlapping of interventions may have created cumulative or interactive effects on the behaviour of fuel prices which are not fully isolated in the present model. The ARIMA modelling framework assumes linear relationships and may inadequately capture more complex dynamics in fuel price behaviour, especially during periods of economic instability. The analysis primarily emphasises the intervention effect and does not explicitly account for other determinants of fuel prices, such as international crude oil prices, exchange rate fluctuations, and macroeconomic conditions.

These limitations may be overcome in future studies by adding more explanatory variables to capture the broader determinants of fuel price dynamics and to improve the model's robustness. Researchers may also use alternative modelling techniques such as nonlinear time series models or structural break models that can better capture complex fuel price responses. Future research may also examine different intervention points to differentiate between stages of pandemic-related policy measures, and conduct cross-country comparisons to improve the generalisability of the results and better understand the economic effects of mobility restrictions.

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