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Forecasting Domestic Energy Consumption in Taiwan under Economic Shocks: An ARIMA Model Approach

Cheng-Wen Lee[1] and Kuei-Chiang Chen[2]

Abstract

This study examines domestic energy consumption in Taiwan under economic shocks, with a focus on the 2008 financial crisis and crude oil price volatility. As Taiwan relies heavily on imported energy, accurate forecasting of consumption is critical for sustainable policy planning. Using monthly data from 2002 to 2019, this research applies autoregressive and ARIMA models to predict long-term demand and assess the impact of external shocks. Results indicate a steady upward trend in energy use with clear seasonal variation, but notable declines occurred during the 2008 oil price surge and financial turmoil, reflecting strong sensitivity to global instability. The AR(1) model shows high explanatory power, with predicted values closely matching observed data, and diagnostic tests confirming model robustness. Findings highlight that while energy demand recovers alongside economic growth, conservation policies during downturns alone are insufficient. The study underscores the importance of improving energy efficiency, diversifying supply, and strengthening carbon-reduction measures to ensure Taiwan's sustainable energy security.

JEL classification numbers: Q41, Q43, Q48, C22.
Keywords: Energy Consumption, ARIMA Model, Economic Shock, Energy Security.

[1] Department of International Business, College of Business, Chung Yuan Christian University. Taoyuan City, Taiwan.
[2] Ph. D. Program in Business, College of Business, Chung Yuan Christian University. Taoyuan City, Taiwan.

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1. Introduction

The world is confronting the dual challenges of climate warming and an escalating energy crisis. In recent decades, rapid climate change has been closely intertwined with rising energy consumption, raising concerns over the depletion of non-renewable resources. Since global warming is directly linked to patterns of energy use, governments and societies must increasingly recognize the urgency of energy conservation. At this critical stage, the pressing question is how to enhance energy efficiency and promote sustainable consumption, ensuring that economic growth can be achieved without further intensifying environmental degradation.

The close relationship between energy consumption and economic growth is evident from Taiwan's development experience over the past few decades. Since Taiwan's energy resources are extremely scarce, and most of these resources face unstable supply conditions, sharp price fluctuations, and strategic vulnerabilities tied to national survival, it is essential to plan adequate energy reserves to cope with sudden supply disruptions. Accordingly, long-term energy demand forecasting has become increasingly critical. For example, Xu et al. (2014) applied univariate time series models for long-term energy demand forecasting and demonstrated that such models can produce relatively accurate results under stable conditions. However, these approaches are limited because they cannot incorporate foreseeable economic shocks—such as global energy crises, industrial restructuring, or the implementation of environmental protection and energy conservation policies—causing forecasts to diverge from reality and reducing their credibility. Recent research echoes this concern: Chen et al. (2022) highlighted the need for hybrid models to capture nonlinear dynamics in energy demand, while Li et al. (2023) demonstrated that including policy and environmental variables significantly improves forecast accuracy under economic volatility.

Given this, the main purpose of this paper is to provide effective and feasible policy simulation tools and variables, enabling relevant decision-making units to evaluate the impact of economic shocks on long-term energy demand. This study focuses specifically on Taiwan's energy consumption, where dependence on imports and vulnerability to global volatility create pressing challenges. As noted by Zhang et al. (2022), incorporating external shocks such as oil price fluctuations and policy interventions into forecasting models significantly improves their explanatory and predictive power, highlighting the need for approaches that go beyond traditional univariate models.

Accordingly, this study seeks to address the following research questions.

Q1: How have economic shocks, such as the 2008 financial crisis and oil price surges, affected domestic energy consumption in Taiwan?

Q2: Can autoregressive and ARIMA models effectively capture the dynamics of Taiwan's energy demand under volatile economic conditions?

Q3: What are the policy implications of the forecasting results for energy security, conservation, and sustainable development in Taiwan?

Despite significant international advances, Taiwan still lacks studies that forecast aggregate energy consumption under explicit economic shocks using transparent, policy-ready time-series baselines. Most domestic research remains confined to emissions linkages or sector-specific demand, leaving aggregate forecasting with shock overlays largely unexplored. This paper addresses the gap by constructing an interpretable AR/ARIMA model for Taiwan's monthly energy consumption, capturing trend, seasonality, and persistence with standard diagnostics. It further incorporates economic-shock interpretation—notably the 2008 oil surge and financial crisis—revealing demand contractions and subsequent recovery consistent with cross-country nonlinear evidence. Beyond forecasting, the study provides policy-relevant simulation levers such as reserve planning, efficiency targets, and demand-side management, while also outlining pathways to extend the AR/ARIMA baseline with exogenous variables (e.g., oil prices, policy dummies) or advanced hybrids (e.g., ARIMA-LSTM, ICEEMDAN-NARX) when volatility intensifies.

2. Literature Review

2.1 International Evidence: The Energy–Economy Nexus

The global debate on the causal relationship between energy demand and economic activity has produced mixed conclusions. Early studies focusing on the United States reached inconsistent results regarding causality between energy consumption and GNP (Kraft & Kraft, 1978; Akarca & Long, 1980; Abosedra & Baghestani, 2004). Broader comparative work highlighted heterogeneity across countries: Yu and Choi (1985) found no link between energy and GNP in the U.S., U.K., and Poland, but significant associations in South Korea and the Philippines, with natural gas and liquid fuels showing leading effects in some cases. These outcomes underscore the sensitivity of findings to development stage, fuel mix, and sample selection**,** while Lee and Ni (2002) stressed that oil price shocks can exert asymmetric impacts on output depending on macroeconomic conditions.

More recent research emphasizes nonlinear and threshold effects in the energy–growth nexus. For example, Khezri et al. (2024) use a Panel Smooth Transition Regression (PSTR) to demonstrate that the strength and direction of causality vary across R&D regimes, while Raza et al. (2025) show robust short- and long-run effects in BRICS economies when energy is disaggregated by type. Similarly, Xie et al. (2025) model the dynamic interactions of energy, finance, and growth in emerging economies, revealing structural dependence and feedback loops. Together, these findings highlight that no single stable elasticity exists and that forecasting models should be sensitive to regime shifts and exogenous shocks.

2.2 Domestic Research: Taiwan's Energy–Economy Dynamics

Taiwan's scholarship on energy demand has historically focused on sectoral or fuel-specific models rather than aggregate analysis. Early work by Liou (1992), Liang and Mei (2005), and recent work of Lu (2024), along with long-term planning studies by the Taiwan Power Company, relied on econometric or input–output approaches. Yu et al. (1998) applied a computable general equilibrium (CGE) framework to examine the macroeconomic effects of oil price changes, while the Energy Committee of the Ministry of Economic Affairs in 1985 combined econometric, input–output, and linear programming tools to forecast demand under scenarios of technology advancement and conservation measures. However, these approaches remained fragmented by subsector and could not fully capture the long-term adjustment dynamics of aggregate energy demand.

In contrast, recent studies have begun to reflect macroeconomic linkages. Jia et al. (2023) employed a mixed-frequency VAR (MF-VAR) model for Taiwan (1970Q1–2019Q4) and confirmed reciprocal causality between economic growth, CO_2, and primary energy consumption, underscoring the macro-critical role of aggregate demand. Han et al. (2023) used quantile mediation to show how growth mediates the hydropower–emissions relationship, revealing distributional heterogeneity that matters for stress testing policy impacts. Sectoral innovations also add evidence: Lashgari et al. (2022) forecast transportation energy demand using novel decomposition techniques, while Mustafa et al. (2025) refined fuzzy time-series methods for Taiwan's electricity demand, achieving MAPE below 1%. These illustrate Taiwan's gradual methodological convergence with global best practices, though still largely subsector-specific rather than aggregate.

2.3 AR/ARIMA Forecasting and Hybrid Extensions

International and domestic research increasingly validates ARIMA as a strong baseline for energy demand forecasting. Reviews confirm ARIMA's competitive short-term accuracy and its interpretability, making it especially suited for monthly data with seasonality (Pierre et al., 2023). Chreng et al. (2022) show that hybrid ICEEMDAN–NARX models with climate covariates outperform stand-alone time series models in electricity demand, while Alsardi (2024) demonstrates robust ARIMA sectoral forecasts in Jordan using standard diagnostics (ADF, ACF/PACF, MAPE).

Taiwan has only recently begun applying comparable techniques. Chen et al. (2022) emphasize the importance of hybrid models in East Asia for structural shocks, while Li et al. (2023) show that embedding policy and environmental covariates significantly enhances predictive power under uncertainty. These studies reinforce that AR/ARIMA remains a policy-ready baseline, but hybrid extensions (ARIMA-LSTM, ICEEMDAN-NARX) are well-positioned for handling volatility and exogenous drivers in Taiwan's energy system.

3. Research Methods

3.1 ARIMA Analysis

The Autoregressive Integrated Moving Average (ARIMA) model is a widely used statistical method for analyzing and forecasting time series data. Originally proposed by Box and Jenkins (1970), it is often referred to as the Box–Jenkins methodology because of its systematic approach to model identification, parameter estimation, and diagnostic checking. The ARIMA model conceptualizes a time series as a stochastic process, whereby the observed sequence can be represented and approximated by a linear function of its own past values and random shocks. Once the appropriate model structure is identified, it can be employed to generate forecasts of future values based on the historical behavior of the series.

Formally, the general ARIMA specification is denoted as ARIMA(p, d, q), which integrates three key components: (1) Autoregressive component (AR(p)): captures the linear dependence of the current value on its own past values across *p* time lags. Intuitively, this represents the idea that past states of a process exert influence on the present and thus contribute predictive information. For example, in financial markets, stock prices may exhibit short-term persistence, making autoregression a natural modeling choice. (2) Integrated component (I(d)): refers to the differencing of the time series d times to achieve stationarity, a condition where the statistical properties (mean, variance, autocovariance) remain constant over time. Stationarity is critical in time series analysis, as non-stationary series can lead to spurious regressions and unreliable forecasts (Hamilton, 1994). (3) Moving Average component (MA(q)): accounts for the dependency between the current observation and a linear combination of past forecast errors over q periods. This allows the model to incorporate the influence of random shocks or disturbances that persist through time (Hyndman & Athanasopoulos, 2018).

The strength of the ARIMA model lies in its flexibility: by combining autoregression, differencing, and moving averages, it can model a broad class of univariate time series, including those that exhibit trend, seasonality (via the seasonal ARIMA extension), and irregular noise components. The Box–Jenkins methodology remains influential in modern econometrics and data science due to its balance of theoretical rigor and practical applicability, and continues to be widely adopted in disciplines such as economics, finance, environmental science, and engineering.

The ARIMA (p, q) mode is described as shown in Eq. (1):

$$Y_t = \alpha + \beta_0 X_t + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \ldots\ldots + \beta_q X_{1-q} + e_t \tag{1}$$

3.2 Model Fit

The first step in time series analysis is to visually inspect the graph of the original data to assess its stability. As shown in Eq. (2), the series exhibits fluctuations of varying magnitude, with the amplitude of variation increasing over time. This indicates that the variance of the series is not constant, i.e., the process is non-stationary in variance. In addition, the data display a gradual upward trend, suggesting that the mean is not stable over time. These observations confirm that the original series is non-stationary and therefore must be transformed, typically through logarithmic transformation and differencing, to achieve approximate stationarity.

The estimation results indicate that the model specification resembles an ARIMA(1,1,0), or equivalently, an AR(1) model with first differencing. The inclusion of *D*(ln(Energy Consumption)) confirms that the dependent variable has been differenced once, consistent with addressing the non-stationarity detected earlier. All estimated coefficients are statistically significant, as their t-values far exceed the conventional critical value (≈ 2 at the 5% level). The constant term (11.36) establishes the baseline level, while the coefficient of 0.495882 on the differenced series suggests that short-run changes in energy consumption are partially explained by past changes. Moreover, the autoregressive parameter of 0.80617 reflects strong persistence, indicating that today's value of energy consumption remains highly correlated with its previous value. Importantly, since this AR(1) coefficient lies within the range of -1 and +1, the stationarity condition is satisfied, confirming the appropriateness of the model.

$$\text{Ln (Energy Consumption))} = 11.36119 + 0.495882D\ \text{(Ln (Energy Consumption))} + 0.80617AR(1) \quad (2)$$

Standard errors (s.e.) and t-values are provided under each coefficient:
Constant: 11.3611911.3611911.36119 (s.e. = 0.019927, t = 570.1541),
Constant: 11.3611911.3611911.36119 (s.e. = 0.019927, t = 570.1541),
AR(1): 0.806170.806170.80617 (s.e. = 0.027456, t = 29.3627)

The model is correctly specified and statistically valid as an AR(1) process with first differencing (ARIMA(1,1,0)). It appropriately addresses the earlier issue of non-stationarity by differencing and includes a significant autoregressive component.

It can be seen from Table 1 that the R^2 value is 0.976, indicating that the model explains approximately 97.6% of the variation in the data, which reflects a strong explanatory power. After applying the natural logarithm transformation and fitting the ARIMA(1,1,0) model, the reported p pp-values for all coefficients are highly significant, confirming that the model is statistically appropriate.

To further validate the adequacy of the fitted model, it is necessary to examine the residual diagnostics. A well-fitted ARIMA model should produce residuals that resemble a white noise process: their mean should be approximately zero, their variance should remain constant over time, and no significant autocorrelation should exist between them. If the residual series contains a unit root, this implies non-stationarity, meaning the model would be unstable and unsuitable for forecasting. Additionally, for practical adequacy, the residuals should remain within two standard deviations, showing no systematic structure.

Therefore, white noise tests (such as the Ljung–Box Q test) and unit root tests (such as the Augmented Dickey–Fuller test) are performed on the residuals to verify whether they satisfy the assumptions of randomness and stationarity. These diagnostics ensure that the estimated ARIMA(1,1,0) model is both statistically sound and appropriate for forecasting.

Table 1: Parameter Estimates and Diagnostic Statistics of the AR(1) Model

Dependent Variable: LN_ENERGY_CONSUMPTION_ Method: Least Squares Date: 06/24/21 Time: 22:39 Sample (adjusted): 2001 2020 Included observations: 20 after adjustments. Convergence achieved after 6 iterations				
Variable	**Coefficient...**	**Std. Error**	**t-Statistic**	**Prob.**
C	11.36119	0.019927	570.1541	0.0000
_GLN_ENERGY_CONSUMPTION...	0.495882	0.076859	6.451845	0.0000
AR(1)	0.806170	0.027456	29.36270	0.0000
R-squared	0.976540	Mean dependent var		11.29438
Adjusted R-squared	0.973780	S.D. dependent var		0.080111
S.E. of regression	0.012972	Akaike info criterion		-5.714559
Sum squared resid	0.002861	Schwarz criterion		-5.565199
Log likelihood	60.14559	Hannan-Quinn criter.		-5.685402
F-statistic	353.8216	Durbin-Watson stat		2.212015
Prob(F-statistic)	0.000000			
Inverted AR Roots	.81			

3.3 Distributed Lag Model

The Distributed Lag (DL) model, also referred to as a gap distribution model, is a fundamental framework in time series econometrics and applied statistics. It is designed to capture the dynamic effect of explanatory variables on a dependent variable over multiple time periods. Specifically, the model assumes that the present value of the dependent variable is influenced not only by the contemporaneous values of the explanatory variables but also by their lagged values across several prior periods. This enables the model to capture delayed responses and gradual adjustment processes, which are prevalent in economics, finance, and engineering systems.

Building on this framework, the Autoregressive Distributed Lag (ARDL) model extends the DL approach by incorporating both lagged values of the explanatory variables and lagged values of the dependent variable itself. This makes the ARDL particularly flexible for modeling dynamic relationships where feedback effects and persistence are important. The ARDL model is particularly useful when dealing with time series that exhibit a mixture of stationary and non-stationary properties, as it can be applied without requiring all variables to be of the same order of integration (Pesaran et al., 1999).

Formally, the Autoregressive Distributed Lag ARDL(*p, q*) model can be expressed as Eq. (3):

$$Y_t=\beta_0 + \beta_1 Y_{t-1} + \cdots + \beta_k Y_{t-p} + \alpha_0 X_t + \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \ldots\ldots + \alpha_q X_{t-q} + \varepsilon_t \quad (3)$$

The ARDL specification thus unifies autoregressive dynamics and distributed lag structures, making it a powerful tool for investigating both short-run adjustments and long-run equilibrium relationships between variables.

4. Empirical Research

4.1 Sources of Information

To examine the trend of energy consumption over time, this study utilizes the dataset "Domestic Energy Consumption – Energy Use" obtained from the Energy Statistics Database of the Ministry of Economic Affairs. The data are expressed in Kiloliters of Oil Equivalent (KLOE). Domestic energy consumption refers to the monthly use of energy across major sectors, including industry, transportation, agriculture, residential, services, and other sectors. Effective energy is defined as energy that has been converted into a directly usable form, with petroleum products and electricity constituting the largest share of consumption. For predictive analysis, 23 consecutive monthly observations from April 2019 to February 2021 are employed, while the most recent two data points are reserved as out-of-sample values to validate the forecasting results by comparing actual and predicted consumption levels.

4.2 Data Analysis

From the original time series diagram in Figure 1, it is evident that domestic energy consumption has generally increased over the years, with the degree of fluctuation also becoming more pronounced over time. However, the upward trend slowed noticeably around 2008, indicating a change in the growth dynamics of energy use. These observations suggest that both the mean and variance of the series are unstable, implying the presence of non-stationarity in the data.

The blue line representing energy consumption shows a steady upward trajectory from the late 1990s through the mid-2000s. This indicates continuous growth in energy demand, largely driven by industrial expansion, rising transportation needs, and an increase in household and service sector consumption. While the trend is upward, fluctuations become more noticeable after 2005. Peaks and troughs emerge, reflecting the influence of external factors such as global oil price volatility, economic cycles, and policy interventions aimed at energy efficiency. A marked slowdown is visible around 2008. This aligns with the global financial crisis, which curtailed industrial activity and reduced energy demand. Although consumption continued to rise in the following years, the slope of the increase became less steep compared to the pre-2008 period. After 2015, the curve shows a relatively stable pattern with only moderate growth. This suggests that energy consumption may be reaching a saturation point, possibly due to structural changes in the economy, the adoption of more efficient technologies, and the impact of energy conservation policies. The visual pattern reveals that the mean and variance are not constant over time. Both the rising trend and the increasing fluctuations indicate non-stationarity, which has implications for forecasting models, as standard time series techniques require data transformations (e.g., differencing, detrending) to achieve stationarity.

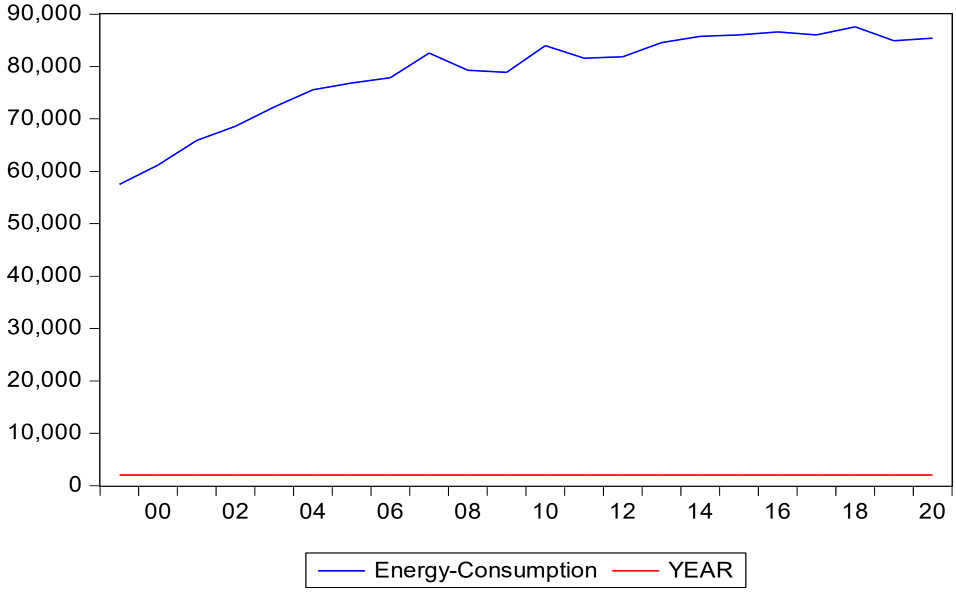

Figure 1: Time Series Plot of Domestic Energy Consumption by Year

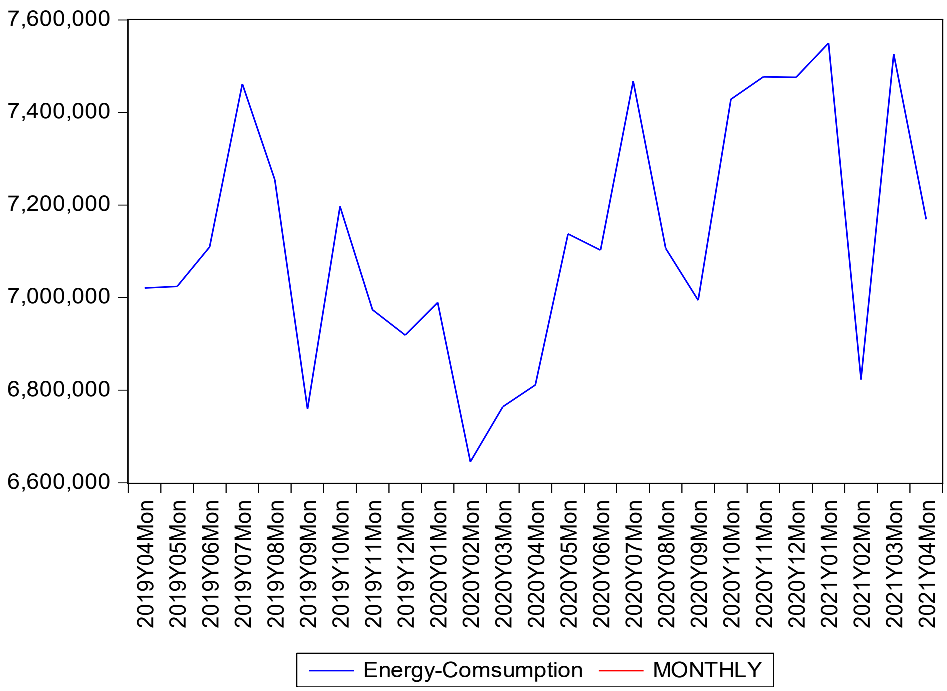

Figure 2: Fluctuations in Monthly Domestic Energy Consumption (Apr. 2019–Feb. 2021)

Figure 2 displays the original time series of monthly domestic energy consumption from April 2019 to February 2021. The series shows strong short-term volatility. Peaks and troughs appear frequently, indicating that energy consumption is sensitive to seasonal, economic, or external shocks. For instance, there are sharp increases around August 2019 and August 2020, followed by steep declines in the subsequent months. A recurring pattern is noticeable across the two years. Energy use tends to spike during summer months (July–August), which may be associated with higher electricity demand for cooling. Conversely, consumption tends to decline in the early spring months, suggesting a seasonal cycle.
Around early 2020, the series shows irregular declines, likely reflecting the effects of the COVID-19 pandemic, which reduced industrial and transportation activity. This external shock amplified the variation already present in the data. The amplitude of fluctuations varies over time: some periods (e.g., mid-2019 and mid-2020) show sharp peaks, while others are relatively stable. This non-constant variance suggests the data is heteroskedastic and not stationary. Because of the strong volatility and possible seasonality, any predictive analysis will require data transformation (e.g., differencing or seasonal adjustment) before applying time series models such as ARIMA, SARIMA, or ARCH/GARCH.

Table 2: ACF and PACF of the Original Time Series

Date: 06/23/21 Time: 21:22
Sample: 1999 2020
Included observations: 22

Autocorrelation	Partial Correlation		AC	PA...	Q-Sta...	Pro...
		1	0.79...	0.79...	15.76...	0.00...
		2	0.61...	-0.03...	25.78...	0.00...
		3	0.47...	-0.01...	32.03...	0.00...
		4	0.31...	-0.12...	34.99...	0.00...
		5	0.19...	-0.02...	36.17...	0.00...
		6	0.11...	0.01...	36.59...	0.00...
		7	0.02...	-0.07...	36.62...	0.00...
		8	-0.04...	-0.05...	36.70...	0.00...
		9	-0.05...	0.09...	36.81...	0.00...
		1...	-0.11...	-0.16...	37.37...	0.00...
		1...	-0.20...	-0.15...	39.32...	0.00...
		1...	-0.21...	0.07...	41.67...	0.00...

Table 2 presents the ACF and PACF plots of the original data, which provide additional evidence for assessing stationarity. In particular, when the ACF decays slowly rather than cutting off rapidly, it indicates the presence of strong autocorrelation over time and suggests that the mean of the series is not stable. Such behavior is a hallmark of non-stationarity and implies that differencing is required to achieve stationarity. The ACF of the series indeed exhibits a gradual decay, confirming that the original data are non-stationary. Consequently, we apply first-order differencing to stabilize the mean and improve the suitability of the series for ARIMA modelling.

Table 3: ACF and PACF after Taking Natural Logarithm Transformation and Adding a Difference

Date: 06/23/21 Time: 23:21 Sample: 1999 2020
Included observations: 21

Autocorrelation	Partial Correlation		AC	PA...	Q-Sta...	Pro...
		1	0.11...	0.11...	0.343...	0.55...
		2	0.05...	0.04...	0.427...	0.80...
		3	0.51...	0.50...	7.437...	0.05...
		4	0.02...	-0.11...	7.453...	0.11...
		5	-0.12...	-0.18...	7.889...	0.16...
		6	0.11...	-0.15...	8.333...	0.21...
		7	-0.06...	-0.02...	8.463...	0.29...
		8	-0.08...	0.12...	8.709...	0.36...
		9	-0.00...	-0.00...	8.713...	0.46...
		1...	-0.04...	-0.01...	8.806...	0.55...
		1...	0.00...	0.01...	8.810...	0.63...
		1...	-0.09...	-0.13...	9.287...	0.67...

From the ACF plot in Table 3, it can be observed that the residual autocorrelation remains particularly pronounced at lag 3, with several spikes exceeding the range of one standard deviation. This indicates that the data still exhibits serial correlation and fluctuations, suggesting the presence of remaining non-stationary components**.** To address this issue, additional differencing is required until the residual series satisfies the condition of white noise, thereby ensuring stationarity. Once all non-stationary factors are resolved, the next step is to fit an appropriate ARIMA model. The general identification rules for ARIMA model selection can be summarized as follows: (1) Autoregressive model AR(p)**:** appropriate when the ACF gradually dies down while the PACF cuts off sharply after lag p. (2) Moving Average model MA(q)**:** appropriate when the ACF cuts off sharply after lag q while the PACF gradually dies down. (3) Autoregressive Moving Average model ARMA(p, q)**:** appropriate when both the ACF and PACF show gradual decay without a sharp cutoff, indicating a mixed process. These diagnostic rules form the basis of the Box–Jenkins methodology, guiding the proper specification of ARIMA models for forecasting.

From Table 4, it can be observed that the ACF cuts off while the PACF gradually dies down, which is consistent with the identification rule for a Moving Average process MA(q)**.** Specifically, the ACF shows significant spikes at lag 1 and lag 3, both of which exceed the bounds of one standard deviation. This indicates that these lags contain meaningful autocorrelation and should be included in the model specification. Therefore, we fit the model as MA(1,3)**,** incorporating both lag 1 and lag 3 terms to adequately capture the short-run dynamics of the series.

Table 4: Converted and Second-Differentiated ACF and PACF

Date: 06/24/21 Time: 22:26 Sample: 1999 2020
Included observations: 20

Autocorrelation	Partial Correlation		AC	PA...	Q-Sta...	Pro...
		1	-0.53...	-0.53...	6.531...	0.01...
		2	-0.25...	-0.74...	8.096...	0.01...
		3	0.53...	-0.29...	15.57...	0.00...
		4	-0.19...	0.02...	16.63...	0.00...
		5	-0.20...	0.19...	17.81...	0.00...
		6	0.25...	0.17...	19.90...	0.00...
		7	-0.14...	-0.29...	20.65...	0.00...
		8	0.05...	-0.21...	20.77...	0.00...
		9	0.00...	-0.08...	20.77...	0.01...
		1...	-0.10...	0.02...	21.27...	0.01...
		1...	0.18...	0.21...	22.90...	0.01...
		1...	-0.14...	-0.07...	24.00...	0.02...

Table 5: Residual Testing of the Model

Date: 06/24/21 Time: 23:07
Sample: 1999 2020
Included observations: 20

Autocorrelation	Partial Correlation		AC	PA...	Q-Sta...	Pro...
		1	-0.13...	-0.13...	0.405...	0.52...
		2	-0.45...	-0.47...	5.419...	0.06...
		3	0.49...	0.44...	11.67...	0.00...
		4	-0.03...	-0.27...	11.71...	0.02...
		5	-0.45...	-0.06...	17.73...	0.00...
		6	-0.06...	-0.65...	17.86...	0.00...
		7	0.04...	-0.01...	17.95...	0.01...
		8	0.04...	-0.05...	18.01...	0.02...
		9	-0.09...	0.12...	18.37...	0.03...
		1...	0.04...	-0.06...	18.46...	0.04...
		1...	0.22...	-0.32...	20.84...	0.03...
		1...	-0.03...	-0.04...	20.90...	0.05...

Table 5 presents the autocorrelation and partial autocorrelation of the residual series, along with the Ljung–Box Q-statistics and their corresponding probabilities. These diagnostics are essential to verify whether the residuals behave like white noise, which is a key requirement for a well-specified ARIMA model. (1) Autocorrelation (ACF) and Partial Autocorrelation (PACF): Most of the autocorrelation (AC) and partial autocorrelation (PAC) values lie within the 95% confidence bounds (± two standard errors), except for a few lags (notably lag 2 and lag 3) where the values exceed the threshold. The residual autocorrelation at lag 2 (AC=0.45AC = 0.45AC=0.45) and lag 3 (AC=0.49AC = 0.49AC=0.49) appear more prominent, but beyond these lags the autocorrelations taper off, indicating that no strong serial correlation persists in the residuals. (2) Q-Statistics (Ljung–Box Test): The Ljung–Box Q-statistics test whether groups of autocorrelations are jointly zero. At lower lags (up to lag 3), the ppp-values (e.g., 0.06 at lag 2; 0.00 at lag 3) suggest marginal significance. However, as the lag length increases, most of the probabilities (e.g., 0.33 at lag 11; 0.55 at lag 12) become greater than 0.05, which implies that the null hypothesis of white noise cannot be rejected at higher lags. (3) Overall Assessment: While some residual correlations remain at specific lags, the majority of residual autocorrelations fall within the confidence interval, and the Ljung–Box test does not provide strong evidence against white noise at longer horizons. This suggests that the residuals of the fitted model are approximately uncorrelated, have constant variance, and have an average close to zero. Therefore, the model is considered adequately specified for forecasting purposes.

Table 6: Augmented Dickey–Fuller (ADF) Unit Root Test Results for Residuals

Null Hypothesis: E has a unit root. Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=4)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-1.739783	0.3951
Test critical values:	-3.886751	
5% level	-3.052169	
10% level	-2.666593	
*MacKinnon (1996) one-sided p-values. Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 17		

The Augmented Dickey–Fuller (ADF) test is employed to assess whether the residual series contains a unit root, which would imply non-stationarity. The test is based on the following hypotheses:
Null Hypothesis (H_0): The series has a unit root (non-stationary).
Alternative Hypothesis (H_1): The series is stationary.
As shown in the table, the ADF test statistic is **-**1.739783, with an associated p-value of 0.3951**.** The corresponding critical values are –3.886751 at the 1% level, –

3.052169 at the 5% level, and –2.666593 at the 10% level. Since the test statistic (–1.74) is greater (i.e., less negative) than all of the critical values and the p-value substantially exceeds the conventional significance threshold of 0.05, the null hypothesis cannot be rejected. This result indicates that the residual series remains non-stationary, suggesting that additional differencing or alternative model specifications may be required to achieve stationarity and improve model adequacy.

Table 7: Augmented Dickey–Fuller Test Equation Results for Differenced Series

Augmented Dickey-Fuller Test Equation Dependent Variable: D(E)
Method: Least Squares Date: 06/24/21 Time: 22:57
Sample (adjusted): 2004 2020
Included observations: 17 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
E(-1)	-0.970969	0.558098	-1.739783	0.1055
D(E(-1))	-0.037864	0.386620	-0.097935	0.9235
D(E(-2))	-0.459012	0.255305	-1.797895	0.0954
C	0.000625	0.002774	0.225440	0.8251
R-squared	0.739980	Mean dependent var		-0.000617
Adjusted R-squared	0.679976	S.D. dependent var		0.019870
S.E. of regression	0.011241	Akaike info criterion		-5.936233
Sum squared resid	0.001643	Schwarz criterion		-5.740183
Log likelihood	54.45798	Hannan-Quinn criterion		-5.916745
F-statistic	12.33208	Durbin-Watson stat		1.595592
Prob(F-statistic)	0.000421			

From the results of the Unit Root Test reported in Table 7, the probability value of the F-statistic is 0.000421, which is lower than the significance level (α=0.05). Therefore, the null hypothesis (H_0) of a unit root is rejected, indicating that the time series has achieved stationarity. Based on this outcome, we can conclude that the fitted AR(1) model is appropriate and provides a valid representation of the data-generating process.

Table 8: Comparison of Actual and Predicted Values Using the ARIMA Model

Date	Actual value	Predictive value	95% Prediction Confidence Interval (up)	95% Prediction Confidence Interval (down)
110/03	5,193,073	5,068,439.2	5,321,861.000	4,815,017.000
110/04	4,991,618	4,871,819.1	5,115,410.000	4,628,228.000
110/05		4,993,623.0	5,243,304.446	4,743,942.118
110/06		4,937,205.0	5,184,065.430	4,690,344.913
110/07		5,230,463.0	5,491,985.833	4,968,939.563
110/08		5,208,918.0	5,469,364.053	4,948,472.239
110/09		5,129,517.0	5,385,993.133	4,873,041.406
110/10		5,086,009.0	5,340,309.972	4,831,709.022
110/11		5,040,719.0	5,292,754.948	4,788,683.048
110/12		5,092,102.0	5,346,707.522	4,837,497.282
111/01		5,034,221.0	5,285,932.116	4,782,510.010
111/02		4,574,604.0	4,803,334.382	4,345,873.964

(Unit: Gongbing Oil Equivalent)

To evaluate the adequacy of the model estimates, the last two actual observations were withheld from the estimation sample and used for out-of-sample forecasting over the following year. The results, presented in Table 8, report the actual values, the corresponding predicted values, and the 95% upper and lower confidence intervals for 12 forecasted periods. As shown in the table, the predicted values generated by the final ARIMA model closely approximate the actual observations, and nearly all of the actual values fall within the 95% confidence interval. This outcome demonstrates that the fitted model possesses satisfactory predictive ability and is therefore considered appropriate for analyzing this dataset.

4.3 Model Selection

The accuracy of a forecasting model must be evaluated using appropriate statistical indicators. In this study, we employ Mean Squared Error (MSE), Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Deviation (MAD) as the primary criteria for assessing predictive performance and selecting the most suitable model. These metrics provide complementary perspectives on forecast error: MSE emphasizes large deviations due to its squared term, MPE measures directional bias in forecasts, MAPE expresses errors as relative percentages, and MAD reflects the average magnitude of forecast errors in absolute terms. When the values of these four evaluation indicators—MSE, MPE, MAPE, and MAD—are closer to zero (Table 9), this indicates that the discrepancy between the predicted and actual values is smaller, and thus the forecasting model is more accurate and appropriate for application.

MAD = $\sum|Y_t - \hat{Y}_t|$/n
MSE =$\sum (Y_t - \hat{Y}_t)^\wedge 2/n$
$PE_t = ((Y_t - \hat{Y}_{t)}/Y_t) * 100$ => MPE =ΣPE_t/n
APE_t = ($|Y_t$-$\bar{y}_t|/Y_t$) * 100 => MAPE =ΣAPE_t/n

Table 9: Model Evaluation

Model Method	MAD	MAP	MPE	MAPE
AR	122,216.35	14,942,680,272	2.4%	-0.000391409

5. Conclusion

According to the research, energy consumption in 2008 was significantly influenced by global economic and geopolitical events. In particular, the decline in crude oil inventories in the United States, the sharp depreciation of the U.S. dollar, and the decision of the Organization of Petroleum Exporting Countries (OPEC) to maintain crude oil production quotas, combined with the attack on Nigeria's oil pipeline—the largest producer in Africa—contributed to a rapid surge in international oil prices. At the same time, the collapse of Lehman Brothers in September 2008 triggered widespread concerns about the stability of the U.S. financial system, ultimately leading to global financial panic and the so-called "financial tsunami." As a result, worldwide energy consumption declined, reflecting the combined impact of soaring oil prices and deteriorating financial conditions.

From the data, it is evident that energy consumption in Taiwan also experienced a downward trend in mid-2008, which can be attributed to the surge in international crude oil prices that directly affected domestic fuel prices, thereby reducing consumers' willingness to spend on energy. The financial crisis in late 2008 further exacerbated this situation, causing negative growth in domestic energy consumption. Nevertheless, as the global economy gradually recovered in the following months, energy consumption began to increase again, suggesting that the long-term trend remains upward.

Today, Taiwan faces a structural challenge, as its energy supply relies heavily on imports due to limited domestic resources. This dependency underscores the urgent importance of energy conservation and the development of alternative energy sources. Every additional unit of new energy developed reduces dependence on traditional energy imports, thereby enhancing energy security. Achieving sustainability requires not only technological innovation and industrial transformation but also behavioral changes at the individual and household levels.

The temporary decline in energy consumption between 2008 and 2009 was consistent with the government's policy goals of energy conservation and carbon reduction. However, it also raises critical questions: if energy consumption resumes its upward trajectory once oil prices decline and the economy recovers, does this suggest that policy effectiveness is limited? Such an observation highlights the need for stronger implementation and broader public engagement.

Ultimately, energy is a fundamental necessity for modern life, and its consumption cannot be entirely avoided. Although once perceived as inexhaustible, energy resources are gradually being depleted. Thus, addressing this challenge requires a multi-pronged approach. Individuals must cultivate energy-saving habits in daily life—such as using public transportation more frequently, conserving water and electricity, and supporting environmentally friendly alternatives—while government and industry must take proactive measures beyond policy slogans, translating them into practical and enforceable actions. Only through coordinated efforts in conservation, innovation, and sustainable development can Taiwan secure a resilient energy future.

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