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Exploring the Forecasting Performance of ARIMA-GARCH- Family and Regime Switching ARIMA Models for Industrial Manufacturing in Pakistan

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ABSTRACT

Forecasting plays a vital role in making effective planning and decisions for policy making in almost every field of life. Modeling the dynamic behavior of price series due to non-stationarity, conditional heteroscedasticity, leverage effect and structural breaks is challenging. This opens the doors to the applications of non-linear models such as Markov Regime Switching, Symmetric and asymmetric generalized autoregressive conditional heteroscedastic (GARCH) models along with commonly used Autoregressive Integrated Moving Average (ARIMA) models. The main aim of this study is to explore the estimating and forecasting performance of Regime Switching ARIMA(MRS-ARIMA) models and ARIMA models with symmetric GARCH, and asymmetric GARCH (EGARCH, TGARCH and PARCH) models for the annual industrial manufacturing output prices in Pakistan. The empirical evidence based on the application of these models to the selected price series revealed that the Markov regime switching model successfully captures the heteroscedasticity depicting the powerfulness of these models. The forecasting performance of asymmetric GARCH models is better than the symmetric GARCH model. Within the family of GARCH models, the ARMA (2, 1)-PARCH (1, 1) perform the best. Overall, MRR- ARMA models provide the best predictive ability among all the models based on AIC. The use of regime switching models should be increased due to the ability to capture structural changes, heteroscedasticity and non-linearity simultaneously.

Keywords: Forecasting, ARIMA, GARCH, Asymmetric, TAGRCH, EGARCH, PARCH, MRS-ARIMA

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INTRODUCTION

Manufacturing is referred to as the production of goods using human labor, machinery, tools, and chemical or biological processing, and formulation. Manufacturing has existed for years and was originally completed by experienced artisans. They worked with juniors and passed down their skills through apprenticeships. Manufacturers formed guilds that would preserve the artisans' trade secrets and privileges. This early manufacturing system was altered when the factory system was introduced in Britain at the start of the industrial revolution in the late 18th century. (See Farooq 2017). Industrialization appeared to be a feasible way to accomplish the lofty and desirable national goals of better citizen quality of life. Industrialization is seen by governments in developing countries as a means of transforming their economies (Ayodele and Falokun 2003). They use industrialization as a weapon to increase national output, reduce disparities in development outcomes, generate revenue for the government, reduce reliance on industrialized countries and, in some situations, reduce fluctuations in foreign exchange profits. These and other goals are sources of conflict, and the necessary trade-off is rarely affected logically. Many governments have overlooked the necessity of constructing industries that are suitable for their environment while wishing to use industrialization to tackle growth in general. Many industries, for instance, are not designed to make better use of labor and other readily available local resources. As a result, industrialization has had little impact on the problem of domestic resource utilization. Nonetheless, many countries saw industrialization as necessary for breaking the cycle of poverty and achieving a dynamic, self-sufficient economy (Ebong, Udoh, & Obafemi, 2014L Raoof et al., 2021).

In Pakistan, manufacturing is the third largest area of the financial system, it accounts for 13 percent of standard employment and GDP contributes 18.5 percent. Small-Scale manufacturing discovered that Large Scale manufacturing (LSM) leads the overall zone, accounting for 12.2 percent of GDP, with the sectoral share accounting for 66% of total GDP (Yan et al., 2020). Slaughtering is the third component of the sector, from 2003 to 2004, which became distinctly involved as a sub-category and its percent of total GDP accounts for 1.4. (See Economy survey 2009-2010).

Pakistan is the world's 3rd largest manufacturer. Pakistan has steadily grown as an industrial hub, with the manufacturing industry contributing to approximately 18 % of GDP. In line with world trade, Pakistan's exports have increased despite the lockdown in Covid -19. Proper public policies help lower the adverse effects of the pandemic. The government is continually analyzing international and internal situations to maintain stability and guide growth in this difficult situation. The country's trade deficit in July-June (2020-21) was $31.076 billion, compared to $23.159 billion in July-June (2019-20). (See annual report Hassan et al., 2020-2021). Pakistan's industrial sector, which engages around 25% of the country's workforce, has increased exponentially since the 1960s when the country relied mostly on light industrial manufacturing textiles, sugar refining and other businesses that used local raw resources. Pakistan is now a diverse producer and exporter. Textiles, cotton processing, petroleum, metal, cement, and fertilizers are the main industries, although the automotive sector has grown significantly in recent years, and medicines, leather, and surgical tools are also important. (See Economy Survey 2018-2019).

Forecasting with appropriate models to obtain accurate forecasts of the industrial manufacturing output will be helpful for the exporters as well as government to increase exports, and make strong decisions in future planning and policy making. By literature review, it is found that linear modeling such as Autoregressive Integrated

Moving Average(ARIMA) models and Autoregressive Distributed Lag (ARDL) model is widely used to estimate and forecast industrial manufacturing output. But mostly, in real life situations many factors such as strikes, political instability, oil price fluctuations, and the exchange rate of Pk. Rs./US $ and many other hidden factors affect industrial manufacturing and caused structural changes and linear modeling techniques are not sufficient to capture the nonlinearities and structural changes. In such a situation, some nonlinear modeling techniques such as GARCH family of models and regime switching models are more appropriate for estimating and forecasting industrial manufacturing outputs. This study is an attempt to overcome this gap.

The goal of this research is to develop a time series model for estimating and forecasting manufacturing output series in Pakistan that will be valuable for the growth of this sector. This study also aims to compare the forecasting performance of three types of time-series models in the context of industrial manufacturing output in Pakistan: Autoregressive Integrated Moving Average (ARIMA) model, family of Generalized Autoregressive Conditional Heteroskedastic (GARCH) models and Markov regime-switching ARIMA models. In the context of the Family of GARCH models we have considered both Symmetric (GARCH model by Bolleslev, 1986) and Asymmetric GARCH models (EGARCH by Nelson, 1991, PARCH models by Ding et al., 1993 and TARCH by Glosten et al., 1993). In The context of regime switching models, Hamilton(1989) approach has been utilized. The remainder of the paper is organized as follows: In Section 2, we briefly discuss different studies conducted by different researchers. In Section 3, the methodologies used in the study have been summarized. The data analysis and discussion are provided in Section 4. Section 5 presents the conclusion derived and recommendations.

LITERATURE REVIEW

Bekhet and Harun (2012) examined the causality relationship between production and energy of industrial manufacturing in Malaysia for the period 1978 to 2009. They considered the production, capital, labor, and energy series. Their empirical results revealed the existence of unidirectional causality, in the long run, running from energy to production. No significant relationship between all variables appears to be in the short run. Mohsen, Chua and Sab (2015) analyzed the determinants of industrial output in Syria over the period 1980 to 2010. In their research, they applied the unit root test(ADF), Granger causality test, Johansen cointegration test, variance decomposition analysis, impulse response functions, and stability tests. Their finding showed that industrial output is positively related to manufactured exports, capital, agricultural output, population, and but negatively related to the oil price.

Wojewodzki (2010) examined the short and long run causality between the household's savings and industrial production in Poland by applying VAR, ARMA and GARCH econometric procedures. Crafts, Leybourne and Mills (1989) constructed a new index of industrial production for Britain for the years 1700-1913 using a structural time model estimated by the Kalman filter. They compare this index with available indices for British economic growth.

Mahmood and Qasim(2009) Numerous studies exist in the literature that has concentrated on comparing the forecasting performance of different linear and nonlinear time series models (Petter, 2001; Boero and Marrocu, 2002; Marcucci, 2005; Pasha et al.,2007; Basheer et al., 2021; Mahmud and Qasim, 2009; Ali, 2013; Devi, 2018; Qasim et al. 2021a; Qasim et al. 2021b). In most of these studies and many others in the literature, nonlinear models reveal better forecasting ability than their linear counterparts.

DATA AND METHODOLOGY

This study is related to the analysis of the manufacturing output price series in Pakistan. Time series data of annual manufacturing output in billions of U.S $ is obtained from the web "www.macrotrend.net" covering the period of 1960 to 2020. The data consist of 61 observations out of which 51 observations ranging from 1960 to 2011 are used for estimation and the remaining observations for 9 years are used for forecast evaluation. Excel and EViews 9 statistical software are used for analysis purposes. While proceeding with this study, the data has been analyzed graphically to assess the structure of the data. Furthermore, to highlight the hidden feature of the data, descriptive measures have been obtained. The stationarity of the data is assessed using Augmented Dickey and Fuller (1979) unit root test.

Univariate ARIMA models have been identified by using ACF and PACF of the residuals. Different tests available in the literature e.g., Lagrange Multiplier (LM) test are applied to test the existence of the ARCH effect and the CUSUM statistic is applied to test the possible structural breaks. To accommodate the possible heteroscedasticity, GARCH models with different orders have been applied. In the context of regime switching models, two state Markov regime switching ARIMA models have been applied. A brief description of the models has been discussed in the forthcoming Subsection.

Models

The types of models applied in this study are ARIMA models with a constant variance; Family of GARCH models with ARIMA model as mean model and with time-varying variance in the context of both symmetric and asymmetric GARCH models; and Markov regime-switching ARIMA models which are governed under an unobserved state variable allowing the parameters of the mean and the variance of a time series to switch from regime to regime. In this Section, we have described briefly the specification of these models

Autoregressive (AR) Process

The linear autoregressive (AR) model of order l denoted by AR(l) is defined mathematically as:

$$W_t = \varpi_1 W_{t-1} + \ldots + \varpi_l W_{t-l} + \varepsilon_t \qquad t = 1, 2, \ldots T$$

where W_t is the annual industrial manufacturing output returns at time t, $\varepsilon_t \sim iid(0, \sigma^2)$ is the error term and T is the sample size.

Moving Average (MA) Process

The moving average model is specified as the linear combination of the current and m preceding error terms. The moving average model of order m denoted by the MA(m) process is given as:

$$W_t = \theta_0 + \theta_1 \varepsilon_{t-1} + \ldots + \theta_l \varepsilon_{t-m} + \varepsilon_t$$

Autoregressive Moving Average(ARMA) Process

ARMA model is the combination of AR and MA models. For *l* and *m* of AR and MA order respectively, the ARMA model denoted by ARMA(*l*, *m*) is specified as:

$$W_t = \varpi_0 + \varpi_1 W_{t-1} + \ldots + \varpi_l W_{t-l} + \theta_1 \varepsilon_{t-1} + \ldots + \theta_l \varepsilon_{t-m} + \varepsilon_t$$

where $\varepsilon_t \sim iid(0, \sigma^2)$ and W_t is stationary time series. In the case of nonstationary time series, it is integrated the series *d* times by taking the difference to convert it into stationary time series and applied the ARMA model to this stationary time series. The resultant model is known as ARMA(*l*, *d*, *m*) model.

Family of GARCH Models

The ARCH and GARCH models firstly proposed by Engle (1982) and generalized by Bollerslev (1986) respectively have been widely used to estimate and forecast time varying variance. The specification of the ARMA- GARCH model is given as:

$$W_t = \varpi_0 + \varpi_1 W_{t-1} + \ldots + \varpi_l W_{t-l} + \theta_1 \varepsilon_{t-1} + \ldots + \theta_l \varepsilon_{t-m} + \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{P} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^2$$

where α_0 the constant term and $\alpha_1, \alpha_1, \ldots, \alpha_P$ are the parameters of the ARCH specification and $\beta_1, \beta_2, \ldots, \beta_q$ are the parameters of the (GARCH) terms, lying between 0 and 1. This specification represents the symmetric behavior of the time varying variance and is unable to capture the asymmetric behavior of time varying volatility. To accommodate this effect we have also applied three asymmetric models in this study and are described below.

EGARCH

Nelson (1991) suggested the exponential GARCH(EGARCH) model known as the first asymmetric model. The specification of this model is expressed in logarithmic to avoid the nonnegative constraints of the GARCH model imposed on the parameters, $\alpha_i^{'}s$ and $\beta_j{'s}$. The specification of this model is given as:

$$\ln\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \left(|\varepsilon_{t-i}| + \delta_i \varepsilon_{t-i}\right) + \sum_{j=1}^{q} \beta_j \, ln\sigma_{t-j}^2$$

where δ_i is the asymmetric parameter. The negative value of δ_i indicate that the change in variance is larger for negative news as compared to positive news.

Threshold GARCH (TGARCH)

The GJR- GARCH, named after Glosten et al.(1993) is another asymmetric GARCH model widely used to accommodate the leverage effect in the variance. The model describes the aspects of positive and negative news on conditional variance differently. The specification of the model is given as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{P} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^2 + \sum_{k=1}^{r} \delta_k \varepsilon_{t-k}^2 \, \tau_{t-k}$$

where $\tau_{t-k} = 1$ if $\varepsilon_t < 0$ and $\tau_{t-k} = 0$ otherwise

3.1.7 Power GARCH (PARCH) model

Ding et al. (1993) derived an asymmetric power GARCH (p, q) model denoted by PARCH(p, q) to model nonlinearities. The specification of this model is given as:

$$\sigma_t^{\gamma} = \alpha_0 + \sum_{i=1}^{p} \alpha_i \left(|\varepsilon_{t-i}| - \delta_i \varepsilon_{t-i}\right)^{\gamma} + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^{\gamma}$$

where δ_i and γ stand for leverage effects and power terms, respectively.

Markov Regime Switching ARMA Model

The main characteristic of a Markov regime switching model is that the process switch from one regime to another under the Markovian property in which the probability of switching the system to the next state depends only on the previous state rather than the whole history. Hamilton's Markov regime switching model is one of the widely used non-linear time series models in the literature. The switching process in this model is governed under an unobservable state variable $\boldsymbol{S_t}$ that follows a first-order Markov chain. In this study, we have applied the Markov Regime Switching ARMA model. Following literature (Gray, 1996; Abdulmuhsin et al., 2021; Nuseir et al., 2020; Asada et al., 2020;Klaasson, 2002, Marcucci, 2005, Qasim et al., 2021a), we have considered two states. Markov regime switching ARMA model may be specified as follows:

$$W_t = \begin{cases} \varpi_0 + \varpi_{11} W_{t-1} + \cdots + \varpi_{1p} W_{t-p} + \theta_{11}\varepsilon_{t-1} + \cdots + \theta_{1q}\varepsilon_{t-q} + \varepsilon_{1t} & for\ S_t = 1 \\ \varpi_0 + \varpi_{21} W_{t-1} + \cdots + \varpi_{2p} W_{t-p} + \theta_{21}\varepsilon_{t-1} + \cdots + \theta_{2q}\varepsilon_{t-q} + \varepsilon_{2t} & for\ S_t = 2 \end{cases}$$

The unobservable variable S_t follows a first order Markovian relationship with the transition matrix.

$$P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix}$$

where $p_{ij} = P(S_t = j | S_{t-1} = i)$ for i, j =1, 2

We have applied the Maximum Likelihood approach to estimate the Markov regime switching transition model see Qasim et al., 2021a and references therein).

RESULT AND DISCUSSION

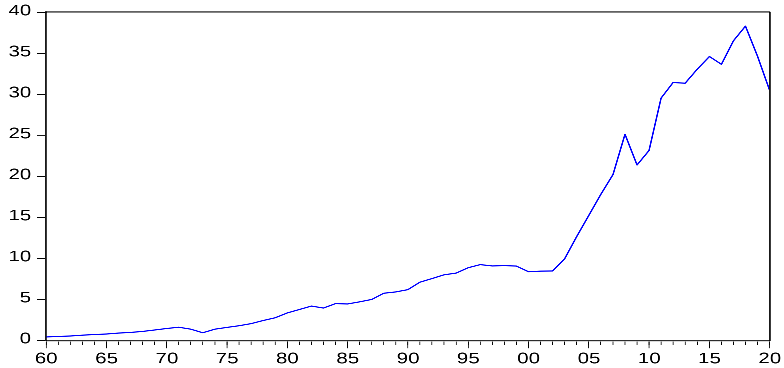


Figure 1: Annual Price of Industrial Manufacturing Output

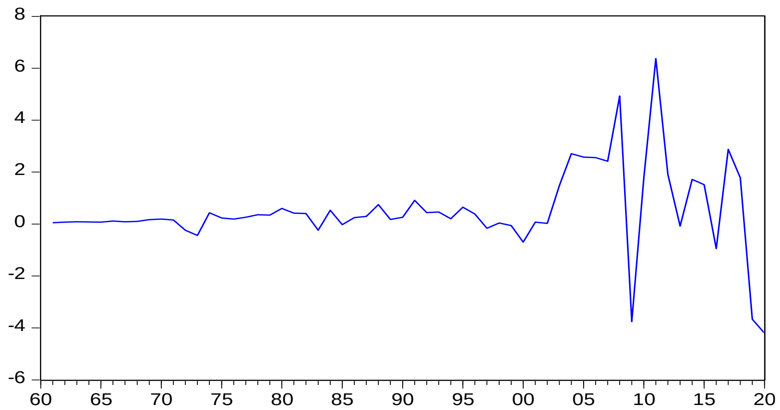


Figure 2: Plot of Industrial Manufacturing Return Series.

As shown in Figure 1, the plot of the annual industrial manufacturing output series (Y_t) presents the increasing trend, showing that the mean of the series is non-constant. As a result, the series is non-stationary. To make the series stationary, the first difference is taken as $W_t = Y_t - Y_{t-1}$ and called it the industrial manufacturing return series. The plot of W_t is depicted in Figure 2 showing that up to 2005 there is no significant variation in the industrial output. However, the upward and downward movements can be seen from 2005 to 2020. Moreover, Figure 2 presents no trend showing the mean of the series is constant and the series is stationary.

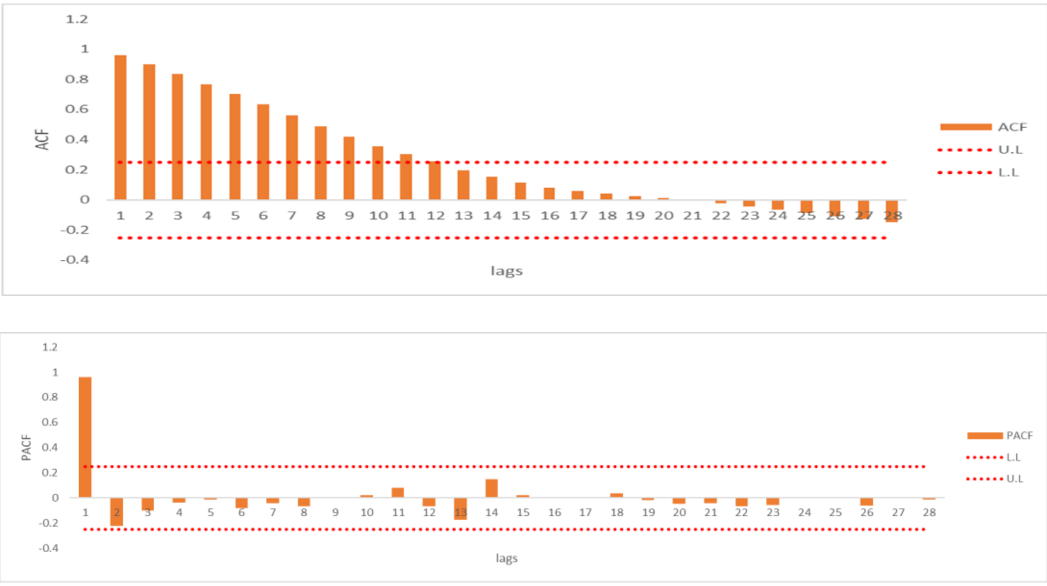


Figure 3: Correlogram of ACF and PACF of Industrial Manufacturing Series

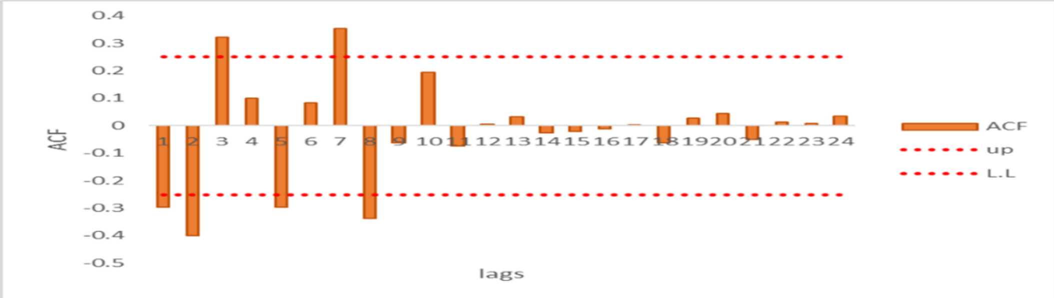


Figure 4: Correlogram of ACF and PACF of W_t

The stationarity of the series is also checked using the unit root test. The Augmented Dickey Fuller unit root test is utilized for this purpose and the results are depicted in Table 1.

Table 1: Unit root test for Industrial Manufacturing Series

	At level		After First Difference	
Series	**t- statistic**	**p-value**	**t-statistic**	**p-value**
Industrial Manufacturing	-2.119045	0.5243	-11.34701	0.000

The unit root test results highlight the p-value greater than the level of significance at 0.01, which leads to the acceptance of the null hypothesis of the existence of unit root in the series revealing the nonstationarity of the series. At first difference, the series shows that the null hypothesis is rejected at a 1% level of significance indicating the stationarity of the series.

Table 2: Descriptive Statistics of Industrial Manufacturing Price Series

Series at level	**Mean**	**Median**	**Std. Dev**	**Skewness**	**Kurtosis**	**Jarque-Bera**	**Probability**
	10.786	6.185	11.62	1.143	2.87	13.346	0.001
At First Difference							
	-0.07	-0.01	1.95	-1.2428	10.267	145.045	0.000

The descriptive statistics of the industrial manufacturing series are displayed in Table 2. These results show that the distribution of series is not normal for both at the level and first difference. After achieving stationarity of the series the Box and Jenkins (1976) methodology has been applied to model the series W_t. To identify the best model, different tentative ARMA models with different orders have been estimated. Diagnostics are checked by observing the correlogram of the residual and squared residual. The values of AIC, BIC, HQ and Loglikelihood function for different ARMA models are reported in Table 3.

Table 3: Model Selection Criteria for ARMA Models

ARMA Models	**AIC**	**BIC**	**HQ**	**Log-likelihood**
ARMA (3,2)	3.994243	4.147205	4.052491	-95.85607

ARMA (1,3)	3.729796	3.882758	3.788045	-89.24490
ARMA (2,1)	3.508504	3.661465	3.566752	-83.71259
ARMA (2,3)	3.962461	4.115423	4.020710	-95.06153
ARMA (0,3)	3.922729	4.037450	3.966415	-95.06821
ARMA (3,1)	3.386958	3.539920	3.445207	-80.67395

The diagnostics criteria are fulfilled for the residuals of these models, except the ACF of the squared residuals is significant at different lags. The ARMA (3,1) is selected as the best model based on the lowest values of AIC, BIC, HQ, and largest Log-likelihood values.

Figure 5: Correlogram of Residuals for ARMA (3,1) Model

Figure 6: Correlogram of Squared Residuals for ARMA (3,1) Model

Figure 5 reveals that ACF and PACF of the residuals show no serial correlation. Figure 6 represents the ACF and PACF of squared residuals and shows that ACF is significant at lags 1, 2 and 3. While PACF is significant at lag 1 and 2 indicating the residuals are conditionally heteroscedastic.The GARCH models are applied to overcome the problem of conditional heteroscedasticity. ARMA models along with GARCH models with different orders are estimated models and observed the diagnostics in terms of ACF and PACF of the residuals and squared residuals. The models satisfying the diagnostics along with the least values of AIC, BIC, HQ and log-likelihood are reported in Table 4.

Table 4: Model Selection Criteria for ARMA-GARCH Model

Model	AIC	BIC	HQ	Log-likelihood
ARMA(3,2)-GARCH (1,1)	1.6833	1.9127	1.7707	-36.0838
ARMA(1,3)-GARCH (1,1)	1.653315	1.8827	1.8827	-35.3328
ARMA(2,1)-GARCH (1,1)	**1.3235**	**1.5887**	**1.4248**	**-26.7501**
ARMA(2,3)-GARCH (1,1)	1.7718	2.0013	1.8592	-38.2971
ARMA(0,3)-GARCH (1,1)	1.6893	1.8806	1.7621	-37.2338
ARMA(3,1) -GRACH (1,1)	1.362530	1.5919	1.4499	-28.0632

The ARMA (2, 1)-GARCH (1,1) model is selected as the best model based on the lowest values of AIC, BIC, HQ, and highest log-likelihood value.

Figure 7: Correlogram of Residuals for ARMA (2, 1) GARCH (1, 1) Model

Figure 8: Correlogram of Squared Residuals for ARMA (2,1) GARCH (1,1) model

Figure 7 and Figure 8 show that the residuals are independent and there is no heteroscedasticity problem left in the series. The estimated results for ARMA(2,1)-GARCH(1,1) are displayed in Table.

Table 5: Estimated Result of ARMA (2, 1)- GARCH (1, 1) Model

Coefficient	Estimates	Std. Error	t-statistic	P-value
ϖ_0	0.0709	0.0261	2.7086	0.0068
ϖ_1	0.1458	2.0603	0.0707	0.9436
ϖ_2	-0.0486	0.8178	-0.0594	0.9526
θ_1	0.1842	1.9559	0.0942	0.9249
		Variance Equation		
α_0	0.000159	0.000555	0.285018	0.7756
α_1	0.760310	0.535480	1.419865	0.1556
β_1	0.714621	0.173107	4.128196	0.0000
ARCH- LM test results				
F-Statistic =	0.1848	P-Value. F(1,48) = 0.6692		
Obs*R-quared =0.1917		P-Value-Chi-Square(1) = 0.6615		

It is obvious that in the mean equation, the coefficient ϖ_0 is highly significant while ϖ_1, ϖ_2 and $\theta_1$are insignificant. In the variance equation, the coefficients α_0 and $\alpha_1$are insignificant while the other is highly significant. Moreover, the results for ARCH-LM test also show that there remains no conditional heteroscedasticity in the residuals.

We have also employed asymmetric GARCH models such as EGARCH, TGARCH and PARCH with different orders. The estimated results for EGARCH, TGARCH and PARCH models are presented in Table 6, Table 7 and Table 8 respectively.

Table 6: Estimate Results of ARMA (2, 1)-TGARCH (1, 2, 1)

Coefficient	Estimates	Std. Error	z-Statistics	p-value
ϖ_0	0.081291	0.008529	9.531286	0.0000
ϖ_1	0.061395	0.046868	1.309941	0.1902
ϖ_2	-0.006376	0.005335	-1.195262	0.2320
θ_1	0.382620	0.147509	2.593878	0.0095
		Variance Equation		
α_0	0.031436	0.043847	0.716945	0.4734
α_1	0.440195	0.453337	0.971011	0.3315
δ_1	0.243668	0.317757	0.766836	0.4432
δ_2	0.587236	0.132386	4.435781	0.0000
β_1	0.144650	0.862789	0.167654	0.8669
ARCH- LM test results				
F-Statistic =3726		P-Value. F(1,48) = 0.5445		
Obs*R-squared = 0.3851		P-Value-Chi-Square(1) = 0.5349		

In the mean equation, the coefficients ϖ_0 and θ_1 are significant while ϖ_1 , ϖ_2 , are insignificant. In the variance equation, the coefficients α_0 ,α_1 , δ_1 and $\beta_1$are insignificant while the other is highly significant. **Table 7: Estimate results of ARMA (2, 1)-EGARCH (1, 2, 1) Model**

Coefficient	Estimates	Std. Error	z-Statistics	p-value
ϖ_0	0.3196	0.1488	2.147767	0.0317
ϖ_1	0.2533	0.2797	0.905664	0.3651
ϖ_2	0.4175	0.0918	4.548442	0.0000

θ_1	-0.0059	0.2544	-0.02344	0.9813
		Variance Equation		
α_0	-3.1771	0.343018	-9.2623	0.0000
α_1	0.9426	0.446429	4.3515	0.0000
δ_1	0.3650	0.296808	1.22984	0.2188
δ_2	-0.2026	0.145261	-1.3949	0.1630
β_1	0.02137	0.3142	3.2504	0.0012

In Table 7, it is obvious that the coefficients ϖ_0 *and* ϖ_2 are significant while ϖ_1 *and* θ_1 are insignificant. Similarly, the coefficients in the variance equation, δ_1 and δ_2 are insignificant while the others are highly significant.

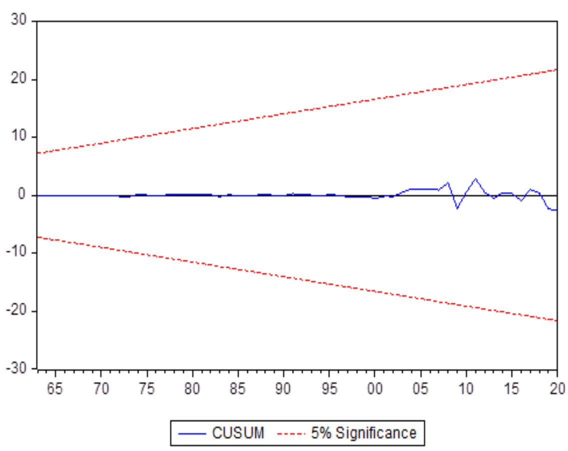
Table 8: Estimate results of ARMA (2, 1)-PARCH (1,1, 1)

Coefficient	Estimates	Std. Error	z-Statistics	p-value
ϖ_0	0.082864	0.012084	6.857125	0.0000
ϖ_1	0.341257	0.791364	0.431227	0.6663
ϖ_2	-0.2473	0.395223	-0.62573	0.5315
θ_1	0.124969	0.713389	0.175177	0.8609
		Variance Equation		
α_0	0.013029	0.026705	0.487906	0.6256
α_1	0.528454	0.507099	1.042111	0.2974
β_1	0.030193	0.413905	0.072946	0.9418
δ_1	0.62853	0.217485	2.889997	0.0039
γ	0.580649	0.914562	0.634893	0.5255

Table 8 represents that in the mean equation, the coefficients ϖ_0 are significant while ϖ_1 , ϖ_2 *and* θ_1 are insignificant. In the variance equation, the coefficients α_0 , α_1, β_1 and γ are insignificant while δ_1 is highly significant indicating that the leverage effect is of significant importance.

Regime Switching ARIMA Modeling

During the initial analysis of data, some structural changes have been observed. Structural changes affect manufacturing outputs due to some political and economic instability. The CUSUM test is most appropriate to check the structural changes in series.



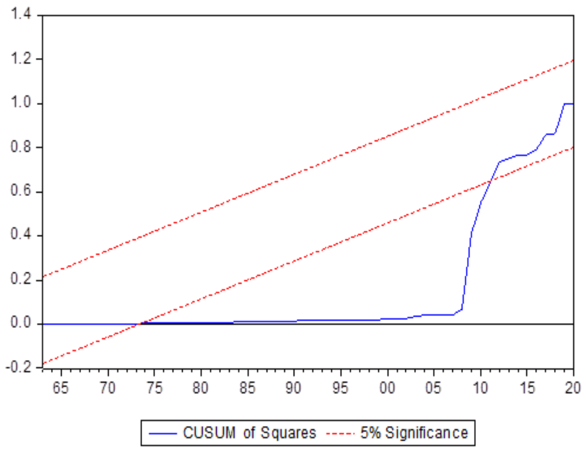


Figure 9: CUSUM of the residuals **Figure 10: CUSUM of Square Residuals**

Figure 9 presents the plot of the cusum residual which lies in critical limits showing no structural breaks. Figure 10 presents the plot of CUSUM of squared residual, which lies outside the significant limits showing the structural break in variance. In modeling and forecasting, linear univariate models, such as ARMA models are unable to capture structural changes. Markov regime switching (MRS) models are the best candidates to handle such situations. In this study, the MRS-ARMA (2, 0) model fulfills the diagnostic and is selected as the appropriate model. The estimation results of this model are given in Table 9.

Table 9: Markov Regime Switching ARMA(2,0) Model – Estimation Results

Coefficient	Estimate	Std.Error	z-statistic	Prob.
		Regime 1		
ϖ_{10}	0.1204	0.0662	1.8185	0.0690
ϖ_{11}	0.2157	0.1746	0.1748	0.2173
ϖ_{12}	0.1746	0.1750	0.1750	0.3187
Log σ_1	-1.2488	0.1255	0.1255	0.0000
${\sigma_1}^2$	0.0823			
		Regime 2		
ϖ_{20}	3.87739	1.1937	3.2480	0.0012
ϖ_{21}	-0.4106	0.3644	-1.1267	0.2599
ϖ_{22}	-0.6066	0.3567	-1.7005	0.0890
Logσ_2	0.7611	0.2654	2.8679	0.0041
${\sigma_2}^2$	4.5823			

Transition Probabilities

Regime	**1**	**2**
1	0.9619	0.0380
2	0.0174	0.9826

Constant Expected Duration

Regime 1	Regime 2
57.4968	26.2991

As displayed in Table 9, for each regime, the log of standard deviation and the constant coefficient is significant. Moreover, the coefficients of second order autoregressive terms in regime 2 are significant with a p-value of 0.089. The importance of regime-switching in the process is also demonstrated by the large values of the transition probabilities. The expected duration of the system remaining in regime 1 is obtained by $1/(1 - p_{11})$ which is 57.4936 years while that for regime 2 computed by $1/(1 - p_{22})$ is 26.297 years. The correlogram of ACF and PACF (not reported here) of residuals and squared residuals has been observed and found no serial correlation and heteroscedasticity. These show the significance of the regime switching models for capturing the dynamics of the series. The selected models along with the values of AIC are reported in Table 10.

Table 10: Model Selection Criteria for Selected Models

Models	**AIC**
ARMA(3,1) -GRACH (1,1)	1.3625
ARMA (2,1)-TGARCH (1,2,1)	1.3522
ARMA (2,1)-EGARCH (1,2,1)	1.7777
ARMA (2,1)-PARCH (1,1,1)	1.1723
MRS-AR (2, 0)	**1.7054**

Table 10 shows that the ARMA (2,1)-PARCH (1,1,1) model is the best model amongst the family of GARCH models applied in this study for the in sample prediction. While overall, MRS-AR(2, 0) model is the best model for in sample prediction according to AIC model selection criteria

Forecast Evaluation

Forecasted values are based on those parameters that are estimated for the prediction. The accuracy of the forecasting model has been assessed by RMSE, MAE, and MAPE. The result is given in Table 11.

Table 11: Forecasting Comparison of Family of GARCH and MAR-ARMA Models

Models	RMSE	MAE	MAPE
ARMA (2,1)-GARCH (1,1)	2.8194	2.3766	100.9135
ARMA (2,1)-TGARCH (1,2,1)	2.8870	2.4131	106.4575
ARMA (2,1)-EGARCH (1,2,1)	3.2704	2.5442	**100.5877**
ARMA (2,1)-PARCH (1,1,1)	**2.7019**	2.3111	105.6599
MRS-ARMA (2, 0)	2.7119	**1.9333**	149.6100

It is obvious from Table 11 that some models are superior to others with respect to some loss functions. No final model can be selected as the best model for forecasting industrial manufacturing series. These results are consistent with many other studies (see Marcucci, 2005 and references therein). However, we recommend the use Markov regime switching ARMA model as these models not only capture the structural changes but also the conditional heteroscedasticity lying under the series.

CONCLUSION AND RECOMMENDATION:

In this study, we have compared the estimating and forecasting abilities GARCH family of models and Markov Regime switching autoregressive integrated moving average models for Industrial Manufacturing prices in Pakistan. Nonstationary, autoregressive conditional heteroscedasticity and structural changes are revealed in the primary analysis of the selected data set. Based on the empirical results, it is found that the symmetric GARCH model provides poor estimating ability than the asymmetric GARCH models. This shows the existence of the leverage effect in the data. Within the family of GARCH models, the ARMA (2,1)-PARCH (1,1,1) perform the best. Overall, MRR- ARMA models provide the best predictive ability among all the models based on AIC. Moreover, it is noticed that the MRS-ARMA models successfully capture the conditional heteroscedasticity.

Based on this study, it is recommended that the use of regime switching models should be increased due to the ability to capture structural changes, heteroscedasticity and non-linearity simultaneously. Moreover, the MRS- ARMA models may also be extended to MRS-ARMAX models with normal and non-normal innovations. These models may also be extended to incorporate the symmetric and asymmetric GARCH models in the regime switching framework.

If the government takes action to promote industrial manufacturing on a small scale as well as large and develops long-term strategies to improve manufacturing performance, a lot of foreign exchange can be earned, and unemployment can be reduced in Pakistan.

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