ARIMA modeling and forecasting of Consumer Price Index (CPI) in Germany

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ABSTRACT

This paper uses annual time series data on CPI in Germany from 1960 to 2017, to model and forecast CPI using the Box – Jenkins ARIMA technique. Diagnostic tests indicate that the GC series is I (1). The study presents the ARIMA (1, 1, 1) model for predicting CPI in Germany. The diagnostic tests further show that the presented parsimonious model is stable and acceptable for predicting CPI in Germany. The results of the study apparently show that CPI in Germany is likely to continue on an upwards trajectory in the next decade. The study encourages policy makers to make use of tight monetary and fiscal policy measures in order to deal with inflation in Germany.

Key Words: Forecasting, Inflation, Germany

JEL Codes: C53, E31, E37, E47

INTRODUCTION

Inflation is one of the central terms in macroeconomics (Enke & Mehdiyev, 2014) as it harms the stability of the acquisition power of the national currency, affects economic growth because investment projects become riskier, distorts consuming and saving decisions, causes unequal income distribution and also results in difficulties in financial intervention (Hurtado *et al*, 2013). As the prediction of accurate inflation rates is a key component for setting the country's monetary policy, it is especially important for central banks to obtain precise values (Mcnelis & Mcadam, 2004).

Consumer Price Index (CPI) may be regarded as a summary statistic for frequency distribution of relative prices (Kharimah *et al*, 2015). CPI number measures changes in the general level of prices of a group of commodities. It thus measures changes in the purchasing power of money (Monga, 1977; Subhani & Panjwani, 2009). As it is a prominent reflector of inflationary trends in the economy, it is often treated as a litmus test of the effectiveness of economic policies of the government of the day (Sarangi *et al*, 2018). The CPI program focuses on consumer expenditures on goods and services out of disposable income (Boskin *et al*, 1998). Hence, it excludes non-market activity, broader quality of life issues, and the costs and benefits of most government programs (Kharimah *et al*, 2015).

To avoid adjusting policy and models by not using an inflation rate prediction can result in imprecise investment and saving decisions, potentially leading to economic instability (Enke & Mehdiyev, 2014). Precisely forecasting the change of CPI is significant to many aspects of economics, some examples include fiscal policy, financial markets and productivity. Also, building a stable and accurate model to forecast the CPI will have great significance for the public, policy makers and research scholars (Du *et al*, 2014). In the case of Germany, the primary goal of the Deutsche Bundesbank is to ensure stability of the price level as outlined in the Bundesbank Law which is hinged on the classical school of economic thought that the main objective of monetary policy is to prevent inflation. The Deutsche Bundesbank is mandated to expand the supply of money and credit with special regard to the stabilization of the price level. This can successfully be achieved when precise CPI values could be obtained through accurate and reliable forecasts. In this study, CPI is used as an indicator of inflation in Germany as we seek to model and forecast CPI using ARIMA models.

LITERATURE REVIEW

In Ireland, Meyler *et al* (1998) forecasted inflation using ARIMA models with quarterly data ranging over the period 1976 to 1998 and illustrated some practical issues in ARIMA time series forecasting. In Finland, Kock & Terasvirta (2013) forecasted consumer price inflation using Artificial Neural Network (ANN) models with a data set ranging over the period March 1960 – December 2009 and established that direct forecasts are more accurate than their recursive counterparts. In case of Malaysia, Kharimah *et al* (2015) analyzed the CPI using ARIMA models with a data set ranging over the period January 2009 to December 2013 and revealed that the ARIMA (1, 1, 0) was the best model to forecast CPI in Malaysia. In an Zimbabwean study, Nyoni (2018) examined inflation using GARCH models with a data set ranging over the period July 2009 to July 2018 and established that there is evidence of volatility persistence for Zimbabwe's monthly inflation data. In the case of Kenya, Nyoni (2018) modeled inflation using ARIMA and GARCH models and relied on annual time series data over the period 1960 – 2017 and found out that the ARIMA (2, 2, 1) model, the ARIMA (1, 2, 0) model and the AR (1) – GARCH (1, 1) model are good models that can be used to forecast inflation in Kenya. In the case of India, Sarangi *et al* (2018) analyzed the consumer price index using Neural Network models with 159 data points and revealed that ANNs are better methods of forecasting CPI in India. Most recently, in a Nigerian study; Nyoni & Nathaniel (2019), based on ARMA, ARIMA and GARCH models; examined inflation in Nigeria using time series data on inflation rates from 1960 to 2016 and found out that the ARMA (1, 0, 2) model is the best model for forecasting inflation rates in Nigeria.

MATERIALS & METHODS

Box – Jenkins ARIMA Models

One of the methods that are commonly used for forecasting time series data is the Autoregressive Integrated Moving Average (ARIMA) (Box & Jenkins, 1976; Brocwell & Davis, 2002; Chatfield, 2004; Wei, 2006; Cryer & Chan, 2008). For the purpose of forecasting inflation rate in Germany, ARIMA models were specified and estimated. If the sequence $\Delta^d GC_t$ satisfies an ARMA (p, q) process; then the sequence of GC_t also satisfies the ARIMA (p, d, q) process such that:

$$\Delta^d GC_t = \sum_{i=1}^{p} \beta_i \Delta^d GC_{t-i} + \sum_{i=1}^{q} \alpha_i \mu_{t-i} + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [1]$$

which we can also re – write as:

$$\Delta^d GC_t = \sum_{i=1}^{p} \beta_i \Delta^d L^i GC_t + \sum_{i=1}^{q} \alpha_i L^i \mu_t + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [2]$$

where Δ is the difference operator, vector $\beta \in \mathbb{R}^p$ and $\alpha \in \mathbb{R}^q$.

The Box – Jenkins Methodology

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018).

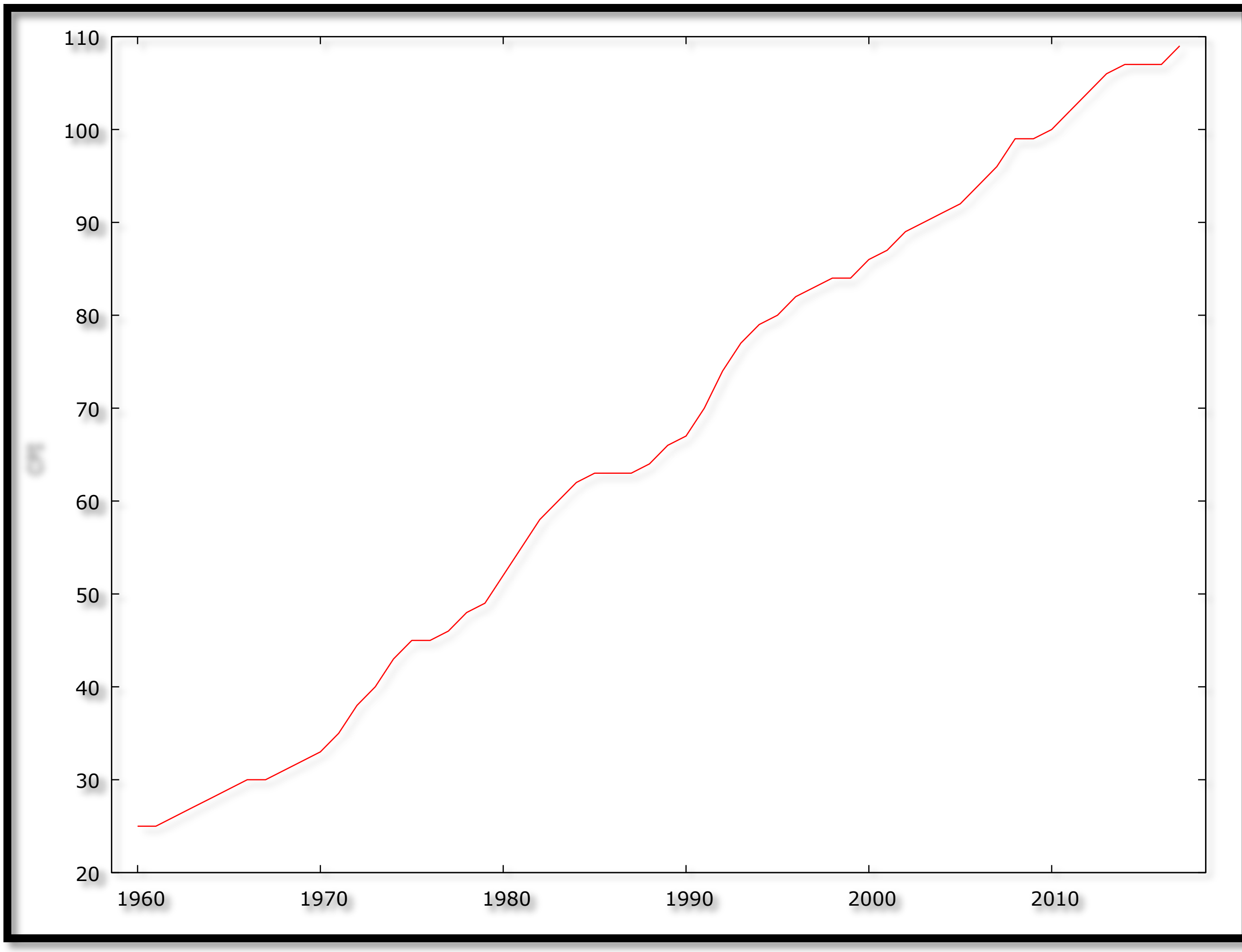
Data Collection

This study is based on a data set of annual CPI (GC) in Germany ranging over the period 1960 – 2017. All the data was taken from the World Bank.

Diagnostic Tests & Model Evaluation

Stationarity Tests: Graphical Analysis

Figure 1



The Correlogram in Levels

Autocorrelation function for CPI ***, **, * indicate significance at the 1%, 5%, 10% levels.

Table 1

LAG	ACF		PACF		Q-stat. [p-value]	
1	0.9558	***	0.9558	***	55.7726	[0.000]
2	0.9101	***	-0.0392		107.2477	[0.000]
3	0.8623	***	-0.0484		154.2996	[0.000]
4	0.8127	***	-0.0467		196.8623	[0.000]
5	0.7623	***	-0.0346		235.0184	[0.000]
6	0.7124	***	-0.0215		268.9872	[0.000]
7	0.6630	***	-0.0242		298.9771	[0.000]

8 0.6129 *** -0.0362 325.1233 [0.000]

9 0.5621 *** -0.0402 347.5635 [0.000]

10 0.5093 *** -0.0559 366.3683 [0.000]

11 0.4575 *** -0.0219 381.8656 [0.000]

The ADF Test in Levels

Table 2: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
GC	-0.363006	0.9079	-3.552666	@1%	Non-stationary
			-2.914517	@5%	Non-stationary
			-2.595033	@10%	Non-stationary

Table 3: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
GC	-3.017324	0.1368	-4.130526	@1%	Non-stationary
			-3.492149	@5%	Non-stationary
			-3.174802	@10%	Non-stationary

Table 4: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
GC	3.000828	0.9992	-2.606911	@1%	Non-stationary
			-1.946764	@5%	Non-stationary
			-1.613062	@10%	Non-stationary

Figure 1 shows that GC is upwards trending and this is a characteristic of non-stationary series. Tables 1 – 4 confirm that GC is indeed non-stationary in levels.

The Correlogram (at 1st Differences)

Autocorrelation function for d_CPI ***, **, * indicate significance at the 1%, 5%, 10% levels.

Table 5

LAG ACF PACF Q-stat. [p-value]

1 0.4056 *** 0.4056 *** 9.8780 [0.002]

2 0.1344 -0.0360 10.9832 [0.004]

3 -0.0813 -0.1477 11.3953 [0.010]

4 -0.1777 -0.1073 13.3995 [0.009]

5 -0.3022 ** -0.2127 19.3076 [0.002]

6 -0.1501 0.0600 20.7928 [0.002]

7	-0.1911	-0.1837	23.2493	[0.002]
8	-0.0292	0.0592	23.3079	[0.003]
9	0.1424	0.1311	24.7279	[0.003]
10	0.2110	0.0289	27.9146	[0.002]
11	0.2059	0.0929	31.0149	[0.001]

ADF Test in 1st Differences

Table 6: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
GC	-4.870860	0.0002	-3.552666	@1%	Stationary
			-2.914517	@5%	Stationary
			-2.595033	@10%	Stationary

Table 7: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
GC	-4.823311	0.0013	-4.130526	@1%	Stationary
			-3.492149	@5%	Stationary
			-3.174802	@10%	Stationary

Table 8: 1st Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
GC	-2.156420	0.0310	-2.606911	@1%	Non-stationary
			-1.946764	@5%	Stationary
			-1.613062	@10%	Stationary

Tables 5 – 8 show that GC became stationary after taking first differences and is thus an I (1) variable.

Evaluation of ARIMA models (without a constant)

Table 9

Model	AIC	U	ME	MAE	RMSE	MAPE
ARIMA (1, 1, 1)	**166.5431**	0.53527	0.2281	0.78552	0.97981	1.3158
ARIMA (1, 1, 0)	167.072	0.54344	0.29549	0.80702	1.0018	1.3467
ARIMA (0, 1, 1)	198.9972	0.73758	0.94507	1.0719	1.3343	1.8151
ARIMA (2, 1, 0)	167.1199	0.53618	0.25329	0.78975	0.98471	1.3228
ARIMA (0, 1, 2)	185.3459	0.65439	0.68828	0.90858	1.16	1.5438

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018). Theil's U must lie between 0 and 1, of which the closer it is to 0, the better the forecast method (Nyoni, 2018). The study will only consider the AIC as the criteria for choosing the best model for forecasting inflation in Germany and therefore, the ARIMA (1, 1, 1) model is carefully selected.

95% Confidence Ellipse & 95% 95% Marginal Intervals

Figure 2 [AR (1) & MA (1) components]

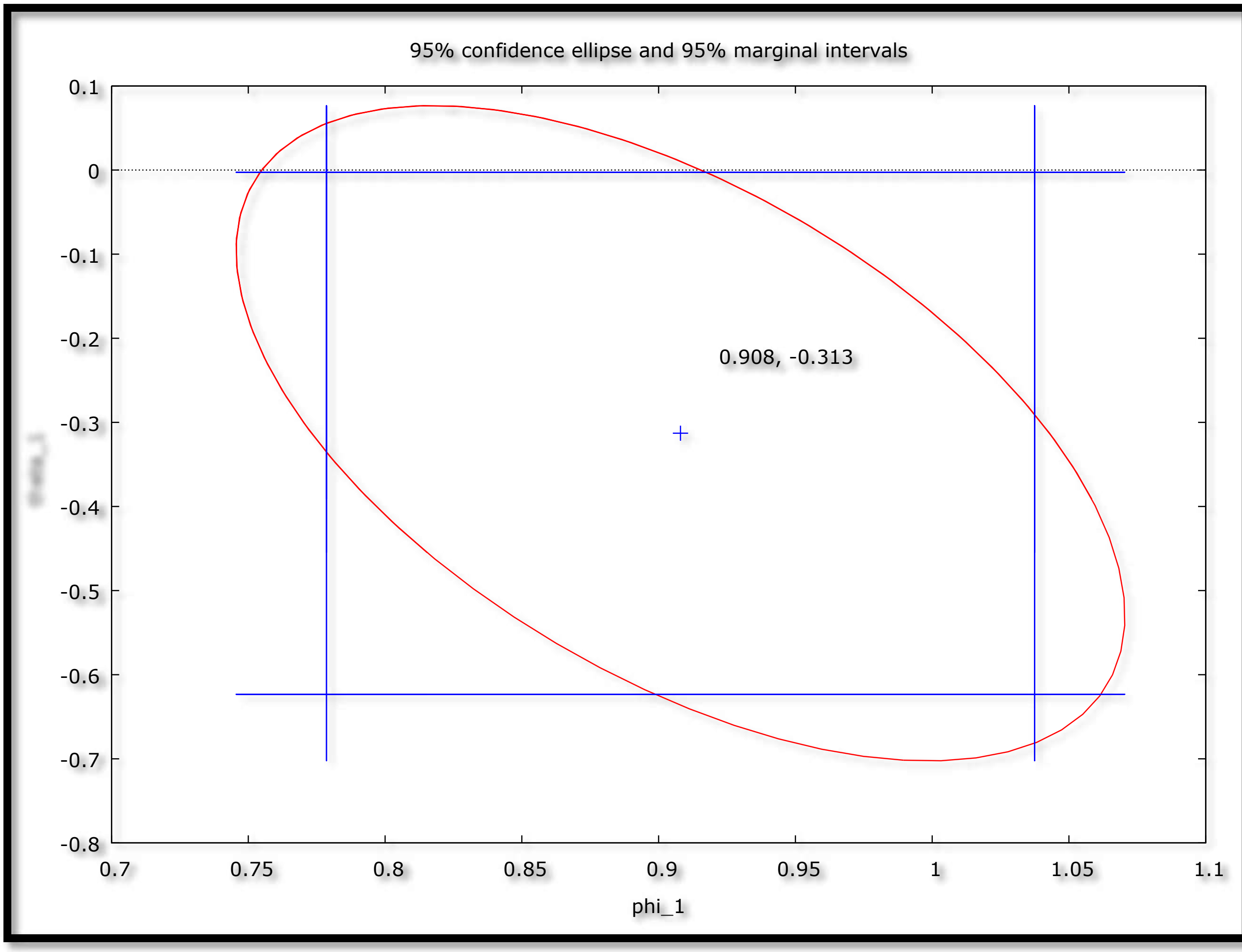


Figure 2 indicates that the accuracy of our forecast, as given the most parsimonious model, the ARIMA (1, 1, 1) model, is satisfactory since it falls within the 95% confidence interval.

Residual & Stability Tests

ADF Tests of the Residuals of the ARIMA (1, 1, 1) Model

Table 10: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-6.939305	0.0000	-3.555023	@1%	Stationary
			-2.915522	@5%	Stationary
			-2.595565	@10%	Stationary

Table 11: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-6.863081	0.0000	-4.133838	@1%	Stationary

		-3.493692	@5%	Stationary
		-3.175693	@10%	Stationary

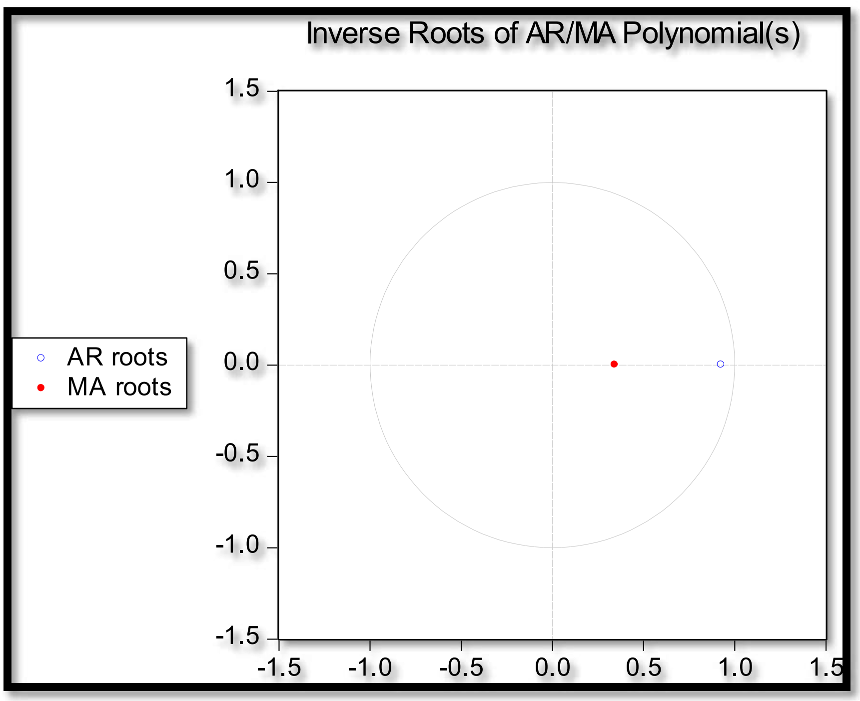
Table 12: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-6.765636	0.0000	-2.607686	@1%	Stationary
			-1.946878	@5%	Stationary
			-1.612999	@10%	Stationary

Tables 10, 11 and 12 show that the residuals of the ARIMA (1, 1, 1) model are stationary and hence the ARIMA (1, 1, 1) model is suitable for forecasting CPI in Germany.

Stability Test of the ARIMA (1, 1, 1) Model

Figure 3



Since the corresponding inverse roots of the characteristic polynomial lie in the unit circle, it illustrates that the chosen ARIMA (1, 1, 1) model is stable and suitable for predicting CPI in Germany over the period under study.

FINDINGS

Descriptive Statistics

Table 13

Description	Statistic
Mean	66.483
Median	65

Minimum	25
Maximum	109
Standard deviation	27.116
Skewness	-0.041385
Excess kurtosis	-1.3298

As shown above, the mean is positive, i.e. 66.48. The minimum is 25 and the maximum is 109. The skewness is -0.041385 and the most striking characteristic is that it is positive, indicating that the inflation series is positively skewed and non-symmetric. Excess kurtosis was found to be -1.3298; implying that the inflation series is not normally distributed.

Results Presentation[1]

Table 14

ARIMA (1, 1, 1) Model:

$$\Delta GC_{t-1} = 0.907993\Delta GC_{t-1} - 0.312904\mu_{t-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [3]$$

P: (0.0000) (0.0433)

S. E: (0.0646) (0.1549)

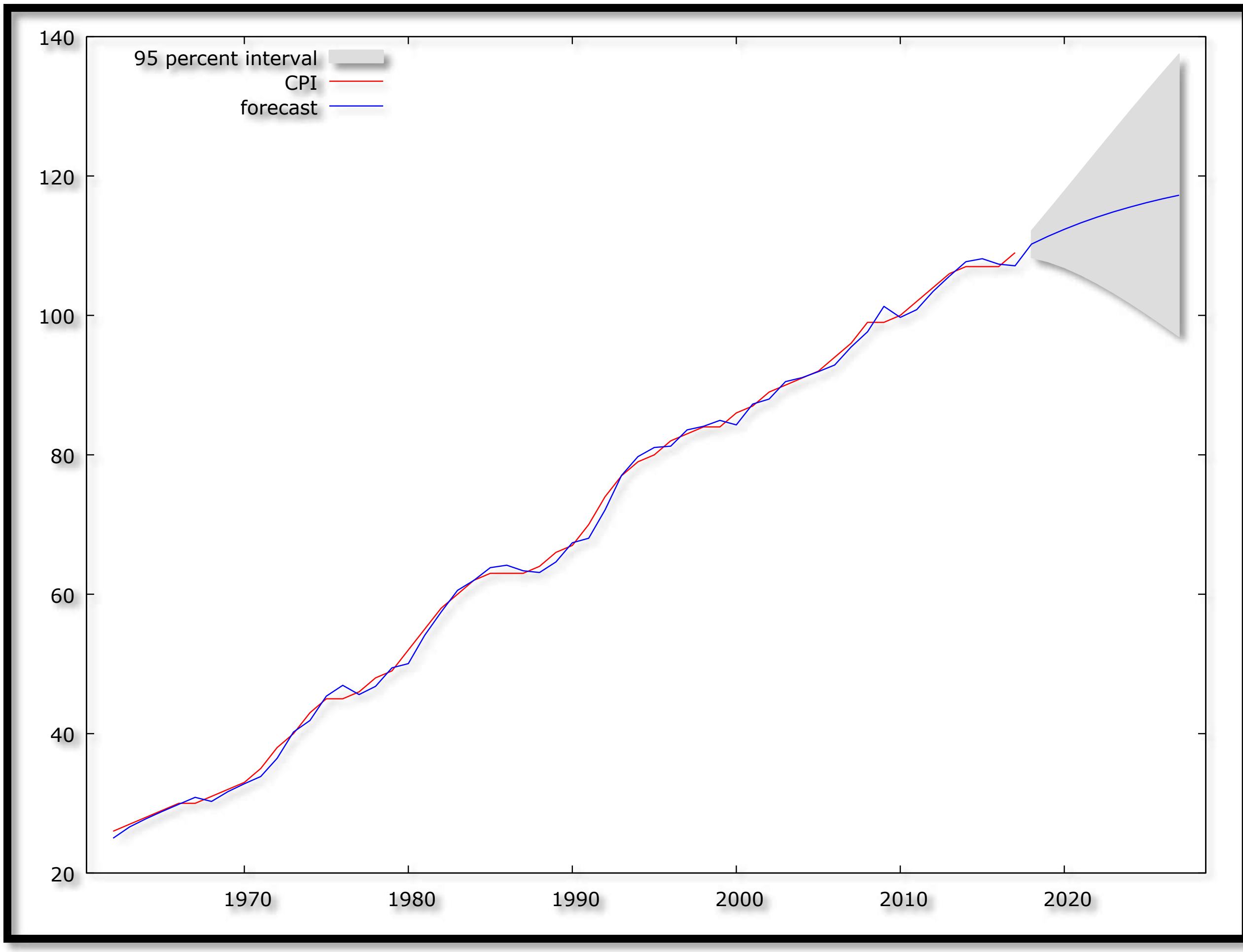
Variable	Coefficient	Standard Error	z	p-value
AR (1)	0.907993	0.0645902	14.06	0.0000***
MA (1)	-0.312904	0.154867	-2.02	0.0433**

The coefficient of the AR (1) component is positive and statistically significant at 1% level of significance. This indicates that previous period CPI indices are important in determining the current and future levels of CPI in Germany. For example, when previous period CPI was relatively high; it arguably causes economic agents (firms, households, workers etc.) to anticipate even higher inflationary pressures in the next period thereby inducing policy ineffectiveness: in the long-run inflation goes up. The results of the study indicate that a 1% increase in the previous period CPI will lead to approximately 0.9% increase in the current period CPI. The coefficient of the MA (1) component is negative and statistically significant at 5% level of significance. This implies that unobserved shocks to CPI have a negative effect on current CPI in Germany. Such shocks may involve but are not limited to monetary policy shocks and desirable political outcomes. The results actually show that a 1% increase in such shocks will lead to approximately 0.31% decrease in CPI, thus a reduced level of inflation. For example, if a new government is elected into power in Germany, through a democratic process; it could lower inflationary expectations and thus enabling policy makers to smoothly engineer disinflation and hence lower CPI levels. The overall striking characteristic of these results is that the coefficient of the AR (1) component is positive while the coefficient of the MA (1) component is negative as conventionally expected and this shows that our model is reasonable and acceptable for forecasting CPI in Germany over the period under study.

Forecast Graph

[1] *The *, ** and *** means significant at 10%, 5% and 1% levels of significance; respectively.*

Figure 4



Predicted Annual CPI in Germany

Table 15

Year	Prediction	Std. Error	95% Confidence Interval
2018	110.22	0.979	108.31 - 112.14
2019	111.34	1.844	107.72 - 114.95
2020	112.35	2.788	106.88 - 117.81
2021	113.26	3.793	105.83 - 120.70
2022	114.10	4.841	104.61 - 123.58
2023	114.85	5.918	103.25 - 126.45
2024	115.54	7.013	101.79 - 129.28

2025	116.16	8.119	100.25 - 132.07
2026	116.73	9.228	98.64 - 134.81
2027	117.24	10.336	96.98 - 137.50

Figure 4 (with a forecast range from 2018 – 2027) and table 15, clearly show that CPI in Germany is indeed set to continue rising sharply, in the next ten years.

POLICY IMPLICATION & CONCLUSION

After applying the Box-Jenkins analysis, the ARIMA was engaged to investigate annual CPI of Germany from 1960 to 2017. The study mostly planned to forecast the annual CPI in Germany for the upcoming period from 2018 to 2027 and the best fitting model was selected based on how well the model captures the stochastic variation in the data. The ARIMA (1, 1, 1) model is stable and most suitable model to forecast the CPI of Germany for the next ten years. In general, CPI in Germany; showed an upwards trend over the forecasted period. Based on the results, policy makers in Germany should engage more proper economic policies in order to fight such increase in inflation as reflected in the forecasts. In this regard, monetary and fiscal authorities are encouraged to engage in tight monetary and fiscal policy measures in order to address the threat of inflation in Germany.

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