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Estimating and forecasting red meat consumption and production in Saudi Arabia during 2022-2030

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The study aims to predict domestic consumption and the production of three meat species (cattle, goats, and sheep) between 2022 and 2030. All series data in addition income per capita as exogenous variable are stationary at the first difference. So vector autoregressive model with exogenous variables $\boldsymbol{VARX(p)}$ was applied, according to information criterion ($\boldsymbol{AIC, BIC}$) the $\boldsymbol{VARX(1)}$ model of order $p\ lag = 1$ without an intercept term and a trend is the best model for predicting domestic meat consumption. Furthermore, the vector autoregressive $\boldsymbol{VAR(3)}$ model with an intercept and trend is the best predictor of meat production for the three types. The predicted value of production for cattle and sheep seems to have fallen throughout the forecast period; conversely, it appears to have increased for goats. On the other hand, cattle and sheep increased in domestic consumption, whereas goats decreased over the estimation period.

Key words: Animal production, animal consumption, forecasting of red meats, vector autoregressive $VAR(p)$ model**,** vector autoregressive with exogenous variable $VARX(p)$ model, unit root test, ADF_n.

INTRODUCTION

Consumer expectations about food taste, quality, diversity, and safety are reflected in demand. In addition, humans have evolved to ingest red meat in vast amounts, particularly lean red meat (McAfee et al., 2010). According to the Organization for Economic Co-operation and Development (OECD) and the Food and Agriculture Organization (FAO) (2021), the consumption of animal proteins in the world is expected to expand by 14% over the next decade, compared to the base period average of 2018-2020. Thus, agricultural output such as red meat has had a vital role throughout these years, particularly in contributing to food security, which has had an influence on the availability of food. However, the situation, particularly with regards to red meats, will worsen since

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there is no effective plan for dealing with unforeseen occurrences and there is less research on food security. Espitia et al. (2020) talk about how there are not enough good red meat policymakers and thorough studies on how the supply of red meat affects food and the decline of food.

Moreover, the consumption of red meat in Saudi Arabia rises as the population expands, which puts pressure on the market for red meat. Thus, the retail market for meat is expected to reach 1.50 billion United States dollar (USD) by 2028, up from 1.31 billion USD in 2022 (Modern Intelligence, 2021). Additionally, in terms of availability and consumption, beef is the most consumed red meat compared to mutton, which occupied the highest consumption among red meats due to its availability at local supermarkets or butcher shops. According to Rosegrant et al. (1999), changes in the fundamental structure of global food demand will cause a massive expansion of food markets as well as a change in consumption patterns as the world's population rises. Particularly, total meat consumption will change as a result of these changes.

This is why Saudi Arabia decided to launch the national industrial development and logistics program (NIDLP). The goal of this institute is to encourage the food industry and farmers to make more food, especially to meet local needs for meat. So, in 2020, red meat production in Saudi Arabia went up by 60% to meet demand and meet the Kingdom of Saudi Arabia's plan to be the fastest-growing edible meat consumer (Modern Intelligence, 2021).

In terms of exporting as well as importing, Saudi Arabia exported $159 million in meat and edible meat offal in 2020, making it the world's 41st largest exporter of meat and edible meat offal. In the same year, edible meat byproducts and meat were Saudi Arabia's 37th most exported commodities. Saudi Arabia imported $1.8 billion in meat and edible meat offal in 2020, making it the world's fourteenth largest importer of meat and edible meat offal. In the same year, edible cow offal and flesh ranked 23rd in Saudi Arabia's imports (OEC 2020).

Vector autoregressive with exogenous variable ($VARX$) model and its important in many applications, is one of the statistical analyses frequently used in many studies involving time series data, such as finance, economics, and business.

The $VARX$ model can explain the dynamic behavior of the relationship between endogenous and exogenous variables or of that between endogenous variables only. $VARX$ can be used to forecast time series data. It is a sophisticated forecasting tool, much better than standard univariate forecasting models, especially in determining the long-run. The $VARX$ model plays an important role in modern techniques of analysis (Hamilton, 1994; Kirchgassner and Wolters, 2007).

Generally, in the case of studies that involve independent or exogenous variables, the VAR model can be easily extended to a VAR model with exogenous variable and referred to as the VAR with exogenous variable or augmented vector autoregressive ($VARX$) model (Hamilton, 1994; Tsay, 2014). The $VARX$ model is also called a dynamic model (Gourieroux and Monfort, 1997). $VARX$ model with linear trend and dummy variable that represents the implementation time of the decision No. (335) related to stopping cultivation of wheat was applied to analyze the dynamic relationship between three time series which includes the areas cultivated with dates, clover, and fodder in Saudi Arabia (Alnashwan and Alderiny, 2017).

Warsono et al. (2019), presented a study that includes the application $VARX(p,q)$, where PTBA and HRUM energy as endogenous variable and exchange rate as an exogenous variable were studied. The data used herein were collected from January 2014 to October 2017. The dynamic behavior of the data was also studied through IRF and Granger causality analyses. The forecasting data for the next 1 month was also investigated. On the basis of the data provided by these different models, it was found that $VARX(3,0)$, is the best model to assess the relationship between the variables considered in this work.

This study forecasts the future of cattle, goat, and sheep meat in Saudi Arabia, examining both their consumption, production and considering exogenous factors like per capita income, which is known to impact the intake of red meat in Saudi society, utilizing the $VARX$ model for prediction. Red meat is one of the most appealing foods consumed by Saudi families in large quantities. It is widely served at public meetings and events, specialty restaurants, fast food restaurants, and other venues, and it comes in a variety of forms and sizes. As a consequence, the predicted quantities of domestic consumption and production in the next few years have become crucial in order to meet Saudi demand. Furthermore, this study deals with the examination and prediction of domestic consumption and production of red meat. Forecasting is the task of fitting a model to historical, time-stamped data in order to predict future values. This research mainly aims to forecast quantities for both red meat consumption and production using different strategies toward planning and predicting red meat consumption and production from the three types (cattle, goats, and sheep) in Saudi Arabia from 2022 to 2030. This objective is achieved through the implementation of a set of sub-objectives, as follows:

Predict domestic consumption of red meat of all three types (cattle, sheep, and goats) using the VAR model in different forms and predict domestic production from red meat of all three types (cattle, sheep, and goats) using the VAR model in different forms.

Table 1. Critical values for test statistics ADF_3 at $\alpha = (0.01, 0.05, 0.10)$.

Case	$\alpha = 0.01$	$\alpha = 0.05$	$\alpha = 0.10$
Trend	-4.15	-3.50	-3.18
drift	-3.58	-2.93	-2.60
Non-intercept	-2.62	-1.95	-1.61

For the level of significance α, $H_0: \tau = 0$ can be rejected if $ADF < ADF_3$ or if the $p.value < \alpha$.

MATERIALS AND METHODS

It was used a vector autoregressive $VAR(p)$ model with exogenous variables $VARX(p, q)$ to forecast red meat production and consumption. This will be done by considering three species, namely cattle, sheep, and goats.

Test for stationary

The validation of the assumption of a stationary state is crucial in the study of time-series data. Various methods exist for identifying the stationary state of time series data, including visual examination via data plots and the use of the augmented Dickey Fuller test (ADF test). The following outlines the procedure for testing the data. According to Tsay (2005) and Rockwell and Davis (2002), let $(y_1, y_2, \ldots, y_T)$ be the time series, and assume that $\{y_t\}$ follows the $AR(p)$ model with mean μ given by:

$$y_t - \mu = \alpha_1(y_{t-1} - \mu) + \alpha_2(y_{t-2} - \mu) + \cdots + \alpha_p(y_{t-p} - \mu) + \varepsilon_t \quad (1)$$

where ε_t is white noise with mean 0 and variance σ^2, and $\varepsilon_t \sim WN(0, \sigma^2)$. The model (Equation 1) can be written as:

$$y_t = \delta + \tau y_{t-1} + \emptyset_1 \nabla y_{t-1} + \cdots + \emptyset_{p-1} \nabla y_{t-p+1} + \varepsilon_t \quad (2)$$

where $\nabla y_t = (y_t - y_{t-1})$, $\delta = \mu(1 - \alpha_1 - \alpha_2 - \cdots - \alpha_p)$, $\tau = (\alpha_1 + \alpha_2 + \cdots + \alpha_p - 1)$, and $\emptyset_j = -(\alpha_{j+1} + \alpha_{j+2} + \cdots + \alpha_p)$, $j = 1, 2, \ldots, p-1$

To test the stationarity of y_t series in model (Equation 2) by using the ADF_n or tau (τ) tests, the null and alternative hypothesis can be written as:

Null hypothesis, $H_0: \tau = 0$ (the series y_t nonstationarity)

Alternative hypothesis, $H_1: \tau < 0$ (the series y_t stationarity) (3)

and ADF_n test statistics is denoted as:

$$ADF = \frac{\hat{\tau}}{se_{\hat{\tau}}} \quad (4)$$

where $\hat{\tau}$ is (OLS) estimate for the τ coefficient in Equation 2, and $se_{\hat{\tau}}$ be computed if the equation has an intercept, and it can also be calculated if the equation has a trend or does not have an intercept. Table 1 illustrates the critical values for ADF_p if $p\ lag = 3$ (Brockwel and Davis, 2002; Tsay, 2005).

Description of VAR and $VARX$ model

The VAR model is a well-recognized model that may be used to analyze the simultaneous equations model in the context of time series data. The VAR model is often used in time-series analysis to investigate the interrelationships among variables. According to Besley and Kontoghiorghes (2009), all variables inside the VAR model are considered endogenous variables. Each variable is determined by its own lag as well as the lag of other variables, resulting in an average value.

Consequently, in order to enhance comprehension of a given variable, it is essential to elucidate its relationship with other variables. Hence, it is essential to do a combined analysis of the variables as suggested by previous studies (Wei, 1990; Hamilton, 1994; Lutkepohl, 2005; Pena et al., 2001). Therefore, it is advantageous to examine any associated time series variables inside a model of system Equations in order to comprehend the underlying factors contributing to the dynamic link between the time series and to improve the precision of forecasts (Pena et al., 2001).

Let vector $\boldsymbol{Y}_t = (Y_{1t}, Y_{2t}, \ldots, Y_{mt})$` of m elements, the general $VAR\ (p)$ model is as follows:

$$\boldsymbol{Y}_t = \boldsymbol{\Phi}_1 \boldsymbol{Y}_{t-1} + \boldsymbol{\Phi}_2 \boldsymbol{Y}_{t-2} + \cdots + \boldsymbol{\Phi}_p \boldsymbol{Y}_{t-p} + \boldsymbol{\varepsilon}_t \quad (5)$$

or

$$\boldsymbol{\Phi}(\boldsymbol{L})\boldsymbol{Y}_t = \left(\boldsymbol{I}_m - \boldsymbol{\Phi}_1 \mathrm{L}^1 - \boldsymbol{\Phi}_2 \mathrm{L}^2 - \cdots - \boldsymbol{\Phi}_p \mathrm{L}^p\right)\boldsymbol{Y}_t = \boldsymbol{\varepsilon}_t \quad (6)$$

where $\mathrm{L}^j \boldsymbol{Y}_t = \boldsymbol{Y}_{t-j}$ and $j = 1, 2., p$ is the backward shift operator, $\boldsymbol{I}_m$ the identity matrix of order m, $\boldsymbol{\Phi}_s = \left[\phi_{l,k}^{(s)}\right]$ is $m \times m$ real matrix , $s = 1, 2, \ldots, p$, and $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t}, \varepsilon_{2t}, \ldots, \varepsilon_{mt})$` is $m \times 1$ errors vector. The $VAR(p)$ model (5) is based on some assumptions determinant Lütkepohl (1991) and Pesaran and Pesaran (1997).

Assumption 1: $\boldsymbol{\varepsilon}_t{'}s$ assumed independent white noise vectors; $\boldsymbol{\varepsilon}_t \sim WN(\boldsymbol{0}, \boldsymbol{\Sigma}_\varepsilon)$ for all t, such that $E(\boldsymbol{\varepsilon}_t) = \boldsymbol{0}$, $E(\boldsymbol{\varepsilon}_t \grave{\boldsymbol{\varepsilon}}_t) = \boldsymbol{\Sigma}_\varepsilon$ for all $t = p, p+1, \ldots, T$, $\boldsymbol{\Sigma}_\varepsilon = [\sigma_{ij}]_{m \times m}$ is an positive definite matrix, and $E(\boldsymbol{\varepsilon}_t \grave{\boldsymbol{\varepsilon}}_{t`}) = 0$ for all $t \neq t$`.

Assumption 2: All the roots, $\left|\boldsymbol{I}_m - \boldsymbol{\Phi}_1 \mathrm{L} - \boldsymbol{\Phi}_2 \mathrm{L}^2 - \cdots - \boldsymbol{\Phi}_p \mathrm{L}^p\right| = \boldsymbol{0}$ are lies outside the unit circle, equivalently, all eigenvalues; λ of companion matrix $\boldsymbol{F}$:

$$\boldsymbol{F} = \begin{pmatrix} \boldsymbol{\Phi}_1 & \boldsymbol{\Phi}_2 & \ldots & \boldsymbol{\Phi}_{p-1} & \boldsymbol{\Phi}_p \\ \mathbf{I}_m & 0 & \ldots & 0 & 0 \\ 0 & \mathbf{I}_m & \ldots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \ldots & \mathbf{I}_m & 0 \end{pmatrix}$$

have modulus less than one; $|\lambda| < 1$, and $\mathbf{I}_m$ is $m \times m$ identity matrix (Hamilton, 1994), then $VAR(p)$ is covariance stationary.

Assumption 3: $(\boldsymbol{Y}_{t-1}, \boldsymbol{Y}_{t-2} \dots, \boldsymbol{Y}_{t-p})$ are not perfectly collinear.

A VAR process can be affected by an exogenous variable; $\boldsymbol{x}_t$, which can be stochastic or nonstochastic. The VAR process can also be affected by the lag of the exogenous variable $\boldsymbol{x}_{t-1}, \boldsymbol{x}_{t-2} \dots, \boldsymbol{x}_{t-q}$. The $VARX(p,q)$ model is expressed by the following Equation:

$$\boldsymbol{Y}_t = \boldsymbol{\delta}_0 + \boldsymbol{\delta}_1 t + \sum_{j=1}^{p} \boldsymbol{\Phi}_j \boldsymbol{Y}_{t-j} + \sum_{k=0}^{q} \boldsymbol{\psi}_k \boldsymbol{x}_{t-k} + \boldsymbol{\varepsilon}_t,$$

$$t = p+1, p+2, \dots, T \quad (7)$$

where $\boldsymbol{\psi}_k = \left[\psi_l^{(k)}\right]$ is of $m \times 1$ real vector, $k = 0,1,2,\dots,q$ can be estimated, t is trend term, $\boldsymbol{\delta}_0$ $m \times 1$ intercepts, and $\boldsymbol{\delta}_1$ $m \times 1$ coefficients of trend intercept.

Assumption 4: $E(\boldsymbol{x}_t, \boldsymbol{x}_{t-1}, \boldsymbol{x}_{t-2} \dots, \boldsymbol{x}_{t-q})` \boldsymbol{\varepsilon}_t = 0$.

Estimation and statistical hypotheses tests

Let $n = T - p$, and $q = 0$, the $VARX(p,q)$ becomes $VARX(p,0)$ or $VARX(p)$ and it can be written in general form of the multivariate linear model as:

$$\boldsymbol{Y}_{n\times m} = \boldsymbol{X}_{n\times k} \mathbf{B}_{k\times m} + \boldsymbol{E}_{n\times m} \quad (8)$$

where $\boldsymbol{Y}_{n\times m} = (\boldsymbol{Y}_{p+1}, \boldsymbol{Y}_{p+2}, \dots, \boldsymbol{Y}_T)`$, $\boldsymbol{X}_{n\times k} = (X`_{p+1}, X`_{p+2}, \dots, X`_T)`$, $X_t = (1, t, \boldsymbol{Y}`_{t-1}, \boldsymbol{Y}`_{t-2}, \dots, \boldsymbol{Y}`_{t-p}, \boldsymbol{x}_t)$, $\boldsymbol{E}_{n\times m} = (\boldsymbol{\varepsilon}_{p+1}, \boldsymbol{\varepsilon}_{p+2}, \dots, \boldsymbol{\varepsilon}_T)`$, $\mathbf{B}_{k\times m} = (B_1, B_2, \dots, B_m)$, $B_j = \beta_l^{(j)}: \left(\delta_{0j}, \delta_{1j}, \phi_{j1}^{(1)}, \phi_{j2}^{(1)}, \dots, \phi_{jm}^{(1)}, \dots, \phi_{j1}^{(p)}, \phi_{j2}^{(p)}, \dots, \phi_{jm}^{(p)}, \psi_j^{(0)}\right)`$, $l = 0,1,\dots,k-1$ and $n = T - p$, $k = 3 + mp$.

Then the conditional least squares (LS) estimator of $\mathbf{B}_{k\times m}$ given by Johnson and Wichern (1992) as:

$$\widehat{\mathbf{B}}_{ls} = (\boldsymbol{X}`\boldsymbol{X})^{-1}\boldsymbol{X}`\boldsymbol{Y} \quad (9)$$

$$\widehat{\boldsymbol{\Sigma}}_\varepsilon = \frac{\left(\boldsymbol{Y} - \boldsymbol{X}\widehat{\mathbf{B}}_{ls}\right)`\left(\boldsymbol{Y} - \boldsymbol{X}\widehat{\mathbf{B}}_{ls}\right)}{n-k}$$ and the estimate of $\boldsymbol{\Sigma}_\varepsilon$ is:

Let $\boldsymbol{\beta} = vec(\mathbf{B})$ denotes the operator that stacks the columns of the $k \times m$ matrix$\mathbf{B}$ into a long $km \times 1$ vector, under assumptions above the $(\widehat{\boldsymbol{\beta}})_{ls} = vec(\widehat{\mathbf{B}}_{ls})$ is consistent and asymptotically normally distributed with asymptotic covariance matrix denoted as:

$$avar(\widehat{\boldsymbol{\beta}})_{ls} = \widehat{\boldsymbol{\Sigma}}_\varepsilon \otimes (\boldsymbol{Q})^{-1}$$

where $(\boldsymbol{X}`\boldsymbol{X})/n$ converges in probability to $\boldsymbol{Q}$, that is:

$$\sqrt{n}\left((\widehat{\boldsymbol{\beta}})_{ls} - \boldsymbol{\beta}\right) \xrightarrow{a} N(\boldsymbol{0}, \widehat{\boldsymbol{\Sigma}}_\varepsilon \otimes (\boldsymbol{Q})^{-1}) \quad (11)$$

The estimation of $avar\left((\widehat{\boldsymbol{\beta}})_{ls}\right)$ becomes:

$$\widehat{avar}\left((\widehat{\boldsymbol{\beta}})_{ls}\right) = \widehat{\boldsymbol{\Sigma}}_\varepsilon \otimes (\boldsymbol{X}`\boldsymbol{X})^{-1} \quad (12)$$

Then the following tests can be performed:

(1) Testing the significance of the regression coefficients $\beta_l^{(j)}$

$null\ hypothesis:$ $H_0: \beta_l^{(j)} = 0$ against

$the\ alternative\ hypothesis: H_1: \beta_l^{(j)} \neq 0,$

the test statistic takes the following equation:

$$t_o = \hat{\beta}_l^{(j)} / S.E_{\hat{\beta}_l^{(j)}} \quad (13)$$

where $\hat{\beta}_l^{(j)}$is the (LS) estimation to coefficient $\beta_l^{(j)}$, $S.E_{\hat{\beta}_l^{(j)}}$ its standard error that computed from $\widehat{avar}\left((\widehat{\boldsymbol{\beta}})_{ls}\right)$ in Equation 13. Under the null hypothesis, the $t_o$test statistics follows a t distribution with $(n-k)$ degrees of freedom.

(2) Likelihood ratio test

Under assumption that the error vectors $\boldsymbol{\varepsilon}_t$ have multivariate normal distribution, the conditional least squares estimator $\widehat{\boldsymbol{\beta}}_{ls}$ is equal to the maximum likelihood estimator of $\boldsymbol{\beta}$. Then we can use Likelihood ratio statistics to test the to constrain $C\boldsymbol{\beta} = r$ as follows:

$null\ hypothesis: H_0: C\boldsymbol{\beta} = r$ against

$the\ alternative\ hypothesis: H_1: C\boldsymbol{\beta} \neq r,$

the test statistic takes the following equation:

$$\chi^2 = -2(LL(H_0) - LL(H_1)) \quad (14)$$

where $LL(H_1)$ log likelihood under H_1 and it denoted by:

$$LL(H_1) = \frac{n}{2} Ln(|\widehat{\boldsymbol{\Sigma}}_{ml}^{-1}| | H_1) - \frac{nk}{2}(Ln2\pi + 1) \quad (15)$$

and $LL(H_0)$ log likelihood under H_0 and it denoted by:

$$LL(H_0) = \frac{n}{2} Ln(|\widehat{\boldsymbol{\Sigma}}_{ml}^{-1}| | H_0) - \frac{nk}{2}(Ln2\pi + 1) \quad (16)$$

then χ^2 in Equation 14 can be rewritten as:

$$\chi^2 = n\left(Ln(|\widehat{\boldsymbol{\Sigma}}_{ml}^{-1}| | H_1) - Ln(|\widehat{\boldsymbol{\Sigma}}_{ml}^{-1}| | H_0)\right) \quad (17)$$

where $\widehat{\boldsymbol{\Sigma}}_{ml}^{-1} = ((n-k)/n)\widehat{\boldsymbol{\Sigma}}_\varepsilon$ is the maximum likelihood estimation to $\boldsymbol{\Sigma}_\varepsilon$, and under the null hypothesis, the χ^2 test statistics follows a $chi.square$ distribution with degrees of freedom; $(number\ of\ coefficients\ under\ H_1 - umber\ of\ coefficients\ under\ H_0)$.

Forecasting

Forecasting is one of the main objectives in the analysis of multivariate time series data. Forecasting in a $VAR(p)$ model is basically similar to forecasting in a univariate $AR(p)$ model. First, the basic idea in the process of forecasting is that the best VAR model must be identified using certain criteria. Once the model is

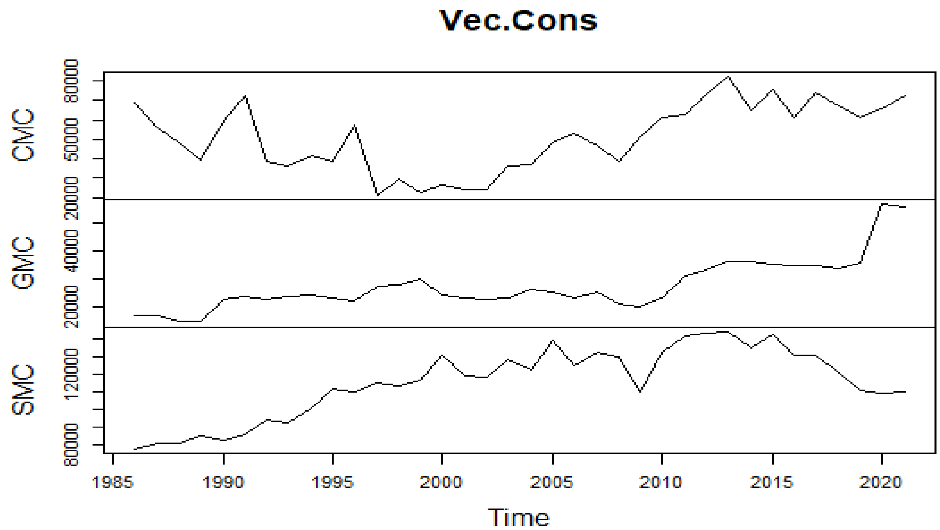


Figure 1. Time curves for meat consumption.

found, it can be used for forecasting. Similarly, the $VARX(p,q)$ model (Equation 7) with the parameters under $q=0$; $(\delta_{0j},\delta_{1j},\phi_{j1}^{(s)},\psi_j^{(0)})$ for $j=1,2,\ldots,m, s=1,2,\ldots,p$ in Equation 7 is assumed to be known. The best predictor, in terms of minimum mean squared error, for $\boldsymbol{Y}_{t+1}$ or 1−step forecast based on the available data at time T is as follows:

$$\hat{Y}_{T+1|T}=\hat{\delta}_0+\hat{\delta}_1(T+1)+\hat{\Phi}_1Y_T+\hat{\Phi}_2Y_{T-1}+\cdots+\hat{\Phi}_pY_{T+1-p}+\hat{\psi}_0x_T \quad (18)$$

Forecasting for longer durations, for example h-step forecast, can be obtained using the chain rule of forecasting as expressed below:

$$\hat{\boldsymbol{Y}}_{T+h|T}=\hat{\boldsymbol{\delta}}_0+\hat{\boldsymbol{\delta}}_1(T+h)+\hat{\boldsymbol{\Phi}}_1\hat{\boldsymbol{Y}}_{T+h-1}$$
$$+\hat{\boldsymbol{\Phi}}_2\hat{\boldsymbol{Y}}_{T+h-2}+\cdots+\hat{\boldsymbol{\Phi}}_p\hat{\boldsymbol{Y}}_{T+h-p}+\hat{\boldsymbol{\psi}}_0\boldsymbol{x}_{T+h} \quad (19)$$

where $\hat{\boldsymbol{Y}}_{T+j}=\boldsymbol{Y}_{T+j}$ for $j\le 0$

Empirical model

In this study let us consider the time series data for Saudi domestic consumption of red meat, specifically for cattle, goats, and sheep, denoted as CMC_t, GMC_t, and SMC_t respectively, at time t. In this context, we can apply the $VARX(p,q)$ model, as represented by Equation 7 to the vector; $\boldsymbol{MC_t}=(CMC_t,GMC_t,SMC_t)$\` if these series stationarity at the same level or to the vector $\Delta\boldsymbol{MC_t}=(\Delta CMC_t,\Delta GMC_t,\Delta SMC_t)$\` if these series stationarity at the first difference with taking into account income per capita symbolled by IPC_t as an exogenous variable at the same level or at the first difference. In the above scenario, the value of m is equal to 3, and q is equal to 0 resulting in the variable $VARX(p,q)$ being represented as either $VARX(p,0)$ or $VARX(p)$. The command "VAR select ()" has been run in program R in order to determine the suitable lag order p.

The study's objectives encompassed the examination of production, imports, and exports of red meat in Saudi Arabia for three types of livestock (cattle, goats, and sheep) from 1986 to 2021. To fulfill these objectives, secondary data from FAO publications were utilized. Additionally, the study involved the calculation of domestic meat consumption MC_t by summing the values of production, imports, and exports over the specified time period.

The per capita income IPC_t data was obtained from the publications of the General Authority for Statistics from 1986 to 2021. The data is included in Appendix 1.

Data description

Figure 1 depicts the time curves for meat consumption and output from the three kinds (cattle, goats, and sheep), as well as revenue per capita. The forms of these curves indicate that the data under consideration is nonstationary. We can see from the meat consumption time curves that the data for cattle meat consumption (CMC) from 1986 to 2002 show a decreasing trend and an increasing trend from 2003 to 2021; the data for goat meat consumption (GMC) from 1986 to 2009 show a stationary trend and an increasing trend from 2010 to 2021; and the data for sheep meat consumption (SMC) during the study years (1986-2021) show an increasing trend.

Figure 2 is regarding production data, we observe that data for both cattle meat production (CMP) and sheep meat production (SMP) exhibited a growing tendency over the study's period (1986-2021), whereas data for goat meat production (GMP) showed the same trend as its consumption data. That is, Saudi production of this kind is almost sufficient to supply local demand without relying on imports. During the study's period (1986-2021), the income per capita (IPC) curve exhibited a growing tendency in Figure 3.

Table 2 presents the descriptive statistics on meat consumption, production, and per capita income. (CMC) has a mean of 51112 tons, with a significant yearly growth rate of 1.5%; (GMC) has a mean of 27579 tons, with a significant annual growth rate of 2.3%; and (SMC) has a mean of 115392 tons, with a significant annual growth rate of 2.3%. For production, the mean (CMP) is 30885

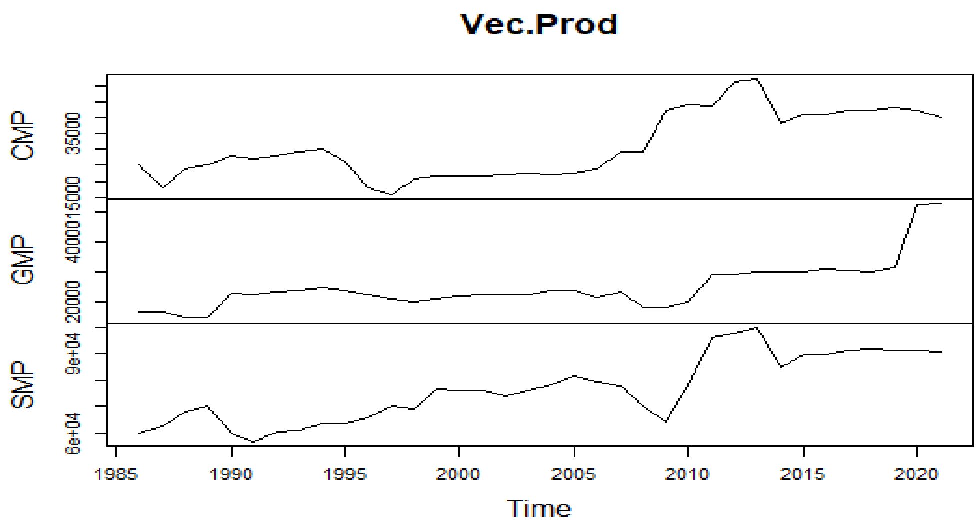


Figure 2. Time curves for meat production.

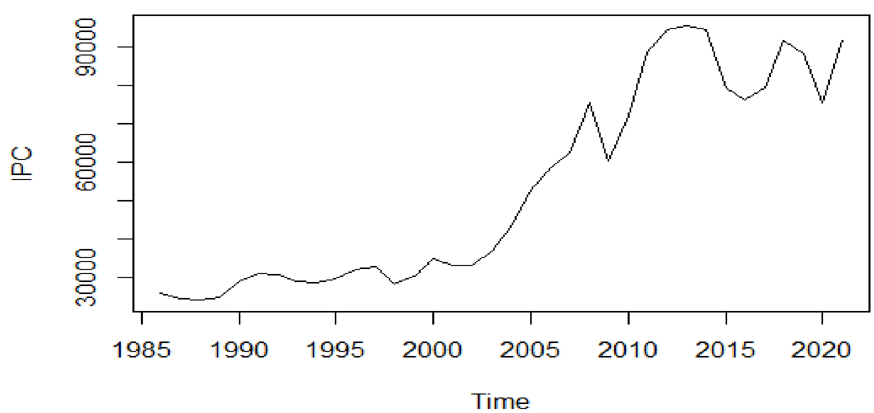


Figure 3. Time curves for income per capita.

Table 2. Some measures of descriptive statistics for meat consumption and production, and income per capita.

Statistical measures	Consumption of meat			Production of meat			Income per capita
	Cattle	Goat	Sheep	Cattle	Goat	Sheep	IPC
Minimum	21647	14700	77288	16000	14700	56434	23973
Maximum	82265	56628	144291	52000	52861	100000	95300
Mean	51112	27579	115392	30885	25126	76379	53226
S. D	17449	9222	19944	10168	8166	12478	26274
gr	0.015**	0.023***	0.013***	0.022***	0.020***	0.014***	0.045***

**grows rat (gr) significant at 0.05, ***grows rat (gr) significant at 0.01.
Source: Computed from Appendix 1.

tons, with a significant annual growth rate of 2.2%; the mean (GMP) is 25126 tons, with a significant annual growth rate of 2.0%; and the mean (SMP) is 76379 tons, with a significant annual growth rate of 1.4%. With a mean (IPC) of 53226 SR over the study period (1986-

Table 3. The computed values of (ADF_n) statistics and critical values at $(\alpha = 0.01, 0.05, 0.10)$.

Series name	Case	Critical values for test statistics at α			ADF_n test statistics					
					At the same level			At first difference		
		0.01	0.05	0.10	Cattle	Goat	Sheep	Cattle	Goat	Sheep
Consumption	Trend	-4.15	-3.50	-3.18	-1.97	-1.41	-0.05	-4.78	-3.32	-3.34
	Drift	-3.58	-2.93	-2.60	-1.14	-0.02	-2.00	-4.77	-3.27	-2.59
	None	-2.62	-1.95	-1.61	0.01	1.59	0.43	-4.81	-2.77	-2.61
Production	Trend	-4.15	-3.50	-3.18	-1.82	-0.87	-4.40	-2.82	-3.09	-5.24
	Drift	-3.58	-2.93	-2.60	-1.07	0.34	-1.21	-2.88	-2.95	-5.32
	None	-2.62	-1.95	-1.61	0.31	1.53	0.53	-2.86	-2.49	-5.17
Income per capita	Trend	-4.15	-3.50	-3.18		-1.89			-3.48	
	Drift	-3.58	-2.93	-2.60		-0.33			-3.53	
	None	-2.62	-1.95	-1.61		1.49			-2.98	

Source: Computed from data in Appendix 1 by using R program.

2021) and a significant annual growth rate of 4.5%.

Stationarity tests

To apply the $VAR(p)$ or $VARX(p,q)$ model in forecasting, the time series in the model under investigation must be validated as stationary, which is done by testing the null and alternative hypotheses in Equation 3. So the command: ur.df(series, type = "trend", "drift", "none," lags = 2) is executed in the R statistical software with the application to all series under investigation to produce the unit root test results using the Augmented Dickey-Fuller(ADF) test. Table 3 summarizes the calculated values of (ADF_n) statistics in Equation 4 and crucial values at significance levels (0.1, 0.05, 0.01). When comparing the computed test statistic of (ADF_n) with the critical values for test statistics in Table 3, we note that according to the findings presented in Table 3, it is evident that the calculated statistics for testing the stationarity of domestic consumption series for cattle, goat, and sheep are lower than the critical values for test statistics in the cases of trend, drift, and non-intercept. Consequently, based on the significance levels (α = 0.01, 0.05, and 0.10), the null hypothesis cannot be rejected.

The outcome indicates that the cattle, goats, and sheep display non-stationarity at the same level. When calculating the first difference for each of the three series data sets, it is observed that the statistics values (ADF_n) corresponding to the cattle meat consumption series in the trend, drift, and non-intercept cases are -4.78, -4.77, and -4.81, respectively. These values exceed the critical values, indicating that the cattle meat consumption series exhibits stationarity at the first difference with a significance level of (α = 0.01, 0.05, 0.10).

On the other hand, the goat meat consumption series at the first difference demonstrates stationarity in the trend case at (α = 0.10), in the drift case at (α = 0.05, 0.10), and in the non-intercept case at (α = 0.01, 0.05, 0.10). Regarding the consumption of sheep meat, the first difference is an indication of stationarity seen in the trend case at a significance level of α = 0.10, in the drift case at α = 0.01, and in the non-intercept case at α = 0.05. Based on previous analyses, it can be deduced that the domestic consumption of red meat, namely cattle, goats, and sheep, exhibits non-stationarity at the same level. However, it demonstrates stationarity when considering the first difference.

The examination of the stationarity of the meat production series for the three varieties of meat may be approached in a way that follows. It is seen that all meat production series exhibit non-stationarity at the same level, with the exception of the sheep meat production series. In the instance of the sheep meat production series, it demonstrates stationarity under the trend assumption at significance levels of 0.01, 0.05, and 0.10. When calculating the first difference for each of all three-time series, it is observed that the corresponding Augmented Dickey-Fuller (ADF_n) statistics values for sheep meat production in the trend, drift, and non-intercept cases are -5.24, -5.32, and -5.17, respectively.

These values exceed the critical values, indicating that the series of sheep meat production becomes stationary at the first difference with a significance level of α = 0.01, 0.05, and 0.10. Conversely, the series of cattle meat production at the first difference is only stationary in the drift case at α = 0.1, and in the non-intercept case at α = 0.01, 0.05, and 0.10. Regarding the analysis of goat meat production series at first difference, it is observed that both the drift case and the non-intercept exhibit stationarity at significance levels of α = 0.05 and 0.10.

Based on prior studies, it can be deduced that the production of red meat from cattle, goats, and sheep exhibits non-stationarity at the same level, with the exception of sheep meat production. However, all three forms of red meat production demonstrate stationarity when considering the first difference. In relation to the data series on income per capita, it is observed that non-stationarity exists at the same level. However, when the time series data is transformed by taking the first difference, it becomes stationary under different scenarios. Specifically, in the trend case, stationarity is achieved at α = 0.1. In the drift case, stationarity is achieved at α = 0.05 and 0.10. Lastly, in the non-intercept case, stationarity is achieved at α = 0.01, 0.05, and 0.10.

RESULTS

Based on the results of the stationary tests, it appears

Table 4. The minimum values of (*IC*) and best $p\ lag$ when *lag max* = 4, *n* = 36.

IC	Both (Trend and constant)		Constant		None intercept		Trend without intercept	
	Min (IC)	p lag	Min (IC)	p lag	Min (IC)	p lag	Min (IC)	p lag
AIC(n)	54.065	1	54.339	1	54.222	1	54.221	1
SC(n)	54.898	1	55.033	1	54.777	1	54.915	1

Source: Computed from data in appendix 1 by using R program.

that all the time series examined exhibit no stationarity at the same level. However, they demonstrate stationarity when considering the first difference. Hence, it proposes to use the $VARX(p,q)$ model, as described in Equation 7, on the first-difference data $\Delta MC_t = (\Delta CMC_t, \Delta GMC_t, \Delta SMC_t)`$ to make predictions about the Saudi consumption of red meat across the three categories.

This prediction is based on the inclusion of the first difference in income per capita ΔIPC_t as an exogenous variable. Furthermore, it has been recommended to use the $VAR(p)$ model, as described in Equation 5, on the first-difference data in order to make predictions on the Saudi production of red meat across the three different categories.

The command "VAR select ()" has been run in program R in order to determine the suitable lag order p. The results pertaining to the information criterion (IC, namely the AIC , and BIC, have been acquired and combined in Table 4.

According to the findings shown in Table 4, it is seen that the lag period $p = 1$ is deemed suitable, as indicated by the information criterion (AIC, BIC) in all four scenarios, namely both constant, non-intercept, and trend. Hence, the use of the $VARX(1)$ model is suggested as a means to anticipate the levels of domestic red meat consumption from 2022 to 2030. Based on the Bayesian Information Criterion (BIC) criteria, the $VARX(1)$model, assuming the absence of an intercept, is identified as the preferred choice for making accurate predictions. The empirical consumption model, referred to as $VARX(1)$, is represented in the following manner in this situation.

$$\begin{pmatrix}\Delta(CMC)_t\\ \Delta(GMC)_t\\ \Delta(SMC)_t\end{pmatrix} = \begin{pmatrix}\emptyset_{11}^{(1)} & \emptyset_{12}^{(1)} & \emptyset_{13}^{(1)}\\ \emptyset_{21}^{(1)} & \emptyset_{22}^{(1)} & \emptyset_{23}^{(1)}\\ \emptyset_{31}^{(1)} & \emptyset_{32}^{(1)} & \emptyset_{33}^{(1)}\end{pmatrix}\begin{pmatrix}\Delta(CMC)_{t-1}\\ \Delta(GMC)_{t-1}\\ \Delta(SMC)_{t-1}\end{pmatrix} + \begin{pmatrix}\psi_1^{(0)}\\ \psi_2^{(0)}\\ \psi_3^{(0)}\end{pmatrix}\Delta(IPC)_t + \begin{pmatrix}\varepsilon_{1t}\\ \varepsilon_{2t}\\ \varepsilon_{3t}\end{pmatrix} \quad (20)$$

The previous model has a system of three equations, with each Equation consisting of four coefficients. The regression coefficient vector for Equation j is denoted as $B_j = \left(\phi_{j1}^{(1)}, \phi_{j2}^{(1)}, \phi_{j3}^{(1)}, \psi_j^{(0)}\right)`, \quad j = 1,2,3.$

The parameters of model 20 are estimated using the conditional least squares (GLS) method, as described in Equation 9 and 10.

The command that is defined as VAR (diff(y), p = 1, type = "none", exogen = diff(x)), is executed. Hence, the findings of the conditional least squares (CLS) estimates for the parameters of the proposed model in Equation 20 are shown in Table 5.

Based on the results mentioned in Table 5, it can be inferred that the following conclusions may be determined:

1. The root of the Equation $\left|I_3 - \widehat{\emptyset}_1 L\right| = 0$ is determined to be $(0.473, 0.329, 0.196)$. It is seen that all roots are located outside the unit circle, indicating that the $VARX(1)$ process exhibits covariance stationarity.
2. The Chi-square test statistics value, obtained using Equation 17, is denoted as $(\chi^2 = 21.12)$. At 12 degrees of freedom, the P-value is calculated to be 0.0487, which is lower than the significance level $(\alpha = 0.05)$. Consequently, the null hypothesis cannot be accepted, leading to the conclusion that the model is suitable for predicting consumption at a significant level of 0.05.

$H_0: VARX(1)\ model\ is\ not\ suitable\ for\ prediction$
$H_1: VARX(1)\ model\ is\ suitable\ for\ prediction$

The equations for predicting red meat consumption for the three categories may be derived in the following manner:

$$\begin{pmatrix}\Delta(\widehat{CMC})_t\\ \Delta(\widehat{GMC})_t\\ \Delta(\widehat{SMC})_t\end{pmatrix} = \begin{pmatrix}-0.365 & 0.403 & -0.120\\ 0.039 & 0.168 & -0.051\\ -0.061 & 0.044 & -0.409\end{pmatrix}\begin{pmatrix}\Delta(CMC)_{t-1}\\ \Delta(GMC)_{t-1}\\ \Delta(SMC)_{t-1}\end{pmatrix} + \begin{pmatrix}0.229\\ -0.118\\ 0.546\end{pmatrix}\Delta(IPC)_t \quad (21)$$

The analysis of autoregressive coefficients ($\emptyset_{ij}^{l}{}'s$) allows for the examination of the impact of the first difference in consumption of three different varieties of meat over the previous period $\Delta(CMC)_{t-1}, \Delta(GMC)_{t-1}, \Delta(SMC)_{t-1}$ as follows:

1. When comparing the domestic consumption of cattle meat in the current period $(CMC)_{t-1}$ to the previous period $(CMC)_{t-2}$, an increase of 1,000 tons is observed. It

Table 5. The estimates of (C*LS*) to parameters of the (1) , *n* = 34.

Variable	Cattle meat consumption $\Delta(\widehat{CMC})_t$			Goat meat consumption $\Delta(\widehat{GMC})_t$			Sheep meat consumption $\Delta(\widehat{SMC})_t$		
	Est.	***t value***	***p value***	***Est.***	***t value***	***p value***	***Est.***	***t value***	***p value***
$\Delta(CMC)_{t-1}$	-0.365	-2.025	0.052	0.039	0.571	0.572	-0.061	-0.503	0.619
$\Delta(GMC)_{t-1}$	0.403	0.757	0.455	0.168	0.840	0.408	0.044	0.124	0.902
$\Delta(SMC)_{t-1}$	-0.120	-0.500	0.621	-0.051	-0.562	0.578	-0.409	-2.551	0.016
$\Delta(IPC)_t)$	0.229	0.656	0.517	-0.118	-0.901	0.375	0.546	2.341	0.026
Roots	0.473	0.329	0.196						
	Covariance matrix of residuals $\hat{\boldsymbol{\Sigma}}_\varepsilon$								
	$\Delta(\mathbf{CMC})$	$\Delta(\mathbf{GMC})$	$\Delta(\mathbf{SMC})$						
$\Delta(CMC)$	1.56E+08	6673311	1107619						
$\Delta(GMC)$	6673311	20376428	2590706						
$\Delta(SMC)$	1107619	2590706	69609860						

Log L_1 = -1051.80, $LogL_0$ = -1062.40, Chi-squares = 21.12, df = 12, p.**value** = 0.0487.
Source: Computed from appendix 1 by using R program.

is anticipated that this increase will result in a significant decrease of 365 tons in the domestic consumption of cattle meat in the current period $(CMC)_t$ compared to the previous period $(CMC)_{t-1}$ at a significance level of 10%. However, it is expected that there will be no significant increase in the domestic consumption of goat meat and a non-significant decrease in sheep meat consumption.

2. In relation to the domestic consumption of goat meat (GMC), when there is a 1,000-ton increase in the previous period $(t-1)$ compared to the preceding period $(t-2)$, it is anticipated that there would be no significant increase in the domestic consumption of cattle meat, and sheep meat individually.

3. Based on the observed increase in sheep meat consumption of 1,000 tons in the past period $(SMC)_{t-1}$ compared to the previous period $(SMC)_{t-2}$, it is anticipated that there will be a statistically significant reduction in domestic sheep meat consumption in the current period $(SMC)_t$ by 409 tons relative to the previous period $(SMC)_{t-1}$ at a significance level of 5%. Additionally, it is anticipated that there will be a statistically insignificant decrease in the consumption of goat meat and cattle meat in domestic consumption.

4. When examining the impact of exogenous changes in income per capita, it is observed that a 1,000 riyal increase in the current period's income per capita $(IPC)_t$ compared to its previous value $(IPC)_{t-1}$ leads to a statistically significant rise in the current domestic consumption of sheep meat $(SMC)_t$ by 546 tons, at a significance level of 5%. However, this increase does not have a statistically significant effect on both domestic consumption of cattle meat $(CMC)_t$ and the domestic consumption of goat meat $(GMC)_t$.

In a general context, the chi-square statistic is computed by using Equation 17 to assess whether the inclusion of the change in income per capita as an exogenous variable enhances the predictive capacity of the $VARX(1)$ model. The value of the statistic, denoted as χ^2_{st}, is equal to 10.192. The probability value, $p.v$, calculated from this distribution with 3 degrees of freedom, is 0.017. This probability value is lower than the specified significance level of 0.05. Therefore, the alternative hypothesis can be accepted, indicating that the inclusion of this exogenous variable enhances the predictive capability of the model 21.

The diagnostic tests

It is necessary to ensure that the residuals derived from estimating the empirical $VARX(1)$ model in Equation 21 adhere to the theoretical assumptions pertaining to the random shocks $\boldsymbol{\varepsilon}_t$, or at the very least, exhibit serious deviations from these assumptions to consider the absence of correlation among the residuals.

To accomplish this task, the following instructions may be executed using the R programming language, as shown in the Table 6.

The instructions listed in Table 6 are executed using the R software, specifically with the application of the empirical model $VARX(1)$. The diagnostic tests pertaining to the residuals of this model are conducted, and the resulting findings are shown and summarized in Table 7.

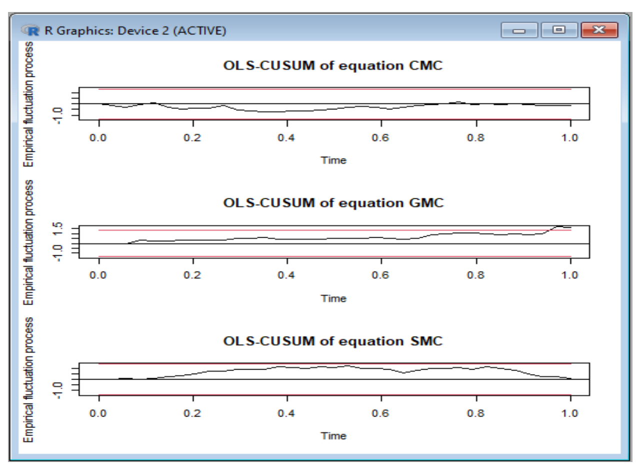
Table 6. The commands related to diagnostic tests for residuals of $VARX(1)$ model in Equation 21.

The name of test	The command
Serial correlation	serial.test (Fit1, lags.pt=5, type= "PT. Asymptotic")
Heteroscedasticity	arch.test (Fit1, lags. multi=5,multivariate.only =TRUE)
Normality	normality.test(Fit1,multivariate.only=TRUE)
Structural breaks	plot (stability (Fit1, type="OLS-CUSUM"))

Table 7. The results of the diagnostic tests of the model $VARX(1)$.

The null hypothesis	Name test	Lag max	Chi square	df	P value
$1. H_0: the\ residuals\ be\ non-autocorrelated.$	Portmanteau (asymptotic)	2	6.97	9	0.64
		3	15.28	18	0.64
		4	18.75	27	0.88
		5	24.91	36	0.92
		10	54.81	81	0.98
$2. H_0: there\ is\ no\ degree\ of\ heteroscedasticity$ or $H_0: \Sigma_{\varepsilon_t} = \Sigma_{\varepsilon_{t-1}} = \cdots = \Sigma_{\varepsilon_1}$	ARCH multivariate	2	70.6	72	0.526
		3	103.1	108	0.616
		4	139.9	144	0.582
		5	174.0	180	0.612
$3. H_0: the\ residuals\ have\ multivariate\ normal$	Jarque-Bera		59.77	3	<0.01

$4. H_0: there\ seems\ to\ be\ no\ structural\ breaks$



From the results in Table 7 it is noted that:

1. The null hypothesis $H_0: the\ residuals\ be\ non-autocorrelated$ cannot be rejected since it reveals that the residuals exhibit no signs of autocorrelation at various lag periods (2, 3, 4, 5, 10). As a result, the model $VARX(1)$ meets the requirement of no serial correlation between the residuals.

2. The second null hypothesis $H_0: there\ is\ no\ degree\ of\ heteroscedasticity$ cannot be rejected either, implying that no ARCH (auto-regressive conditional heteroskedasticity) effects exist in this model.

Table 8. The predicted values of income per capita and consumption of red meat.

year	Income per capita	Cattle meat consum.		Goat meat consum.		Sheep meat consum.	
	$(IPC)_t$	$\Delta(\widehat{CMC})_t$	$(\widehat{CMC})_t$	$\Delta(\widehat{GMC})_t$	$(\widehat{GMC})_t$	$\Delta(\widehat{SMC})_t$	$(\widehat{SMC})_t$
2021	91636*		72181*		55467*		110207*
2022	93518	-2509	69672	-198	55269	305	110512
2023	95400	1230	70902	-369	54900	1046	111558
2024	97282	-292	70610	-290	54609	508	112066
2025	99164	359	70969	-309	54301	824	112890
2026	101046	76	71045	-303	53998	655	113545
2027	102928	202	71248	-304	53694	741	114287
2028	104810	145	71393	-304	53390	698	114985
2029	106692	171	71564	-304	53086	719	115704
2030	108575	159	71724	-304	52783	709	116413
Mean	**101046**		**71014**		**54003**		**113551**
Gr	0.019		0.003		-0.006		0.006

''Initial values
Source: Introduced and computed by the authors from the appendix1.

As a result, the model $VARX(1)$ meets the condition that residuals have stable variance matrices throughout time $\Sigma_{\varepsilon_t} = \Sigma_{\varepsilon_{t-1}} = \cdots = \Sigma_{\varepsilon_1} = \Sigma_{\varepsilon}$.

3. While the third null hypothesis H_0: *the residuals have multivariate normal* cannot be accepted, the residuals of this model seem to be non-normally distributed.

4. The plot of the sum of recursive residuals cumulative sum control chart (CUSUM) reveals that the sum does not exceed the critical boundaries at any point in the graph, indicating that the null hypothesis H_0: *there seems to be no structural breaks* cannot be rejected.

Based on the results of the above study, it is determined that the empirical model passes the most $VARX(1)$ diagnostic tests.

Forecasting of the domestic consumption of red meat for the three types

In order to use the system Equation Inside the empirical Vector Autoregressive $VARX(1)$ model 21 for the purpose of projecting the domestic consumption of red meat from 2022 to 2030, it is necessary to compute the expected value of income per capita as an exogenous variable in Equation 21 as a first step. In this study, the R software's auto.arima() function is used to determine the optimal $ARIMA(p,d,q)$ model. The analysis reveals that the $ARIMA(0,1,0)$ model with a constant term, namely a random walk with a constant, is identified as the most suitable model based on the obtained results. In the present scenario, the expected value $(\widehat{IPC})_{T+h}$ is calculated using the output Equation of the application $\{(\widehat{IPC})_{T+h} = (\widehat{IPC})_{T+h-1} + 1882.057\}$.

In the next stage, the $VARX(1)$ model 21 is used to derive estimated values for domestic red meat consumption, based on the forecasted values of per capita income derived in the first stage. The predict function with the $VARX(1)$ model is executed, specifically with the command dumvar = diff (ICP_future), n.ahead = 9, and ci = 0.95. The resulting output, as shown in Table 8, displays the expected values for income per capita and the forecast values for domestic consumption of red meat across the three categories: cattle, goat, and sheep.

Table 8 shows that the annual mean that is computed to the predicted values of the income per capita during the period 2022–2030 is almost 101,046 SR, with an increase at an exponential growth rate of 1.9% annually. Given the predicted values of income per capita, the predicted values of domestic consumption from cattle meat during the period 2022–2030 have a mean of 71014 tons with an increase annually of 0.3% exponential growth rate, while the predicted values of domestic consumption from goat meat during this period have a mean of 54003 tons and an annual decrease by 0.6% exponential growth rate.

With respect to the predicted values of domestic consumption of sheep meat during this period, it has a mean of 113551 tons, with an increase annually by a 0.6% exponential growth rate. During the examination of the outcomes pertaining to the forecast, it appears that

Table 9. Some statistical indicators (series of first difference; 1987-2021; T=35).

Case	*p* lag	*n*	*LL1*	*LL0*	*Chi_sq. model*	*df*	*p.v*	*AIC*	*BIC*
Non-intercept	1	34	-1006.2	-1007.59	2.816	9	0.971	2030.4	2044.1
Trend & intercept	3	32	-923.2	-949.77	53.158	30	0.006	1912.4	1960.8

Source: introduced and computed by the authors from the appendix1.

Table 10. The predicted values of meat production, the previous predicted values of domestic consumption.

Year	The predicted values of production using $VAR(3)$			The predicted values of consumption using $VARX(1)$		
	Cattle	Goat	Sheep	Cattle	Goat	Sheep
2021*	40000	52861	90578	72181	55467	110207
2022	45434	53607	96278	69672	55269	110512
2023	33584	50614	84406	70902	54900	111558
2024	34670	52764	81404	70610	54609	112066
2025	34847	53981	83737	70969	54301	112890
2026	39316	58950	89992	71045	53998	113545
2027	40371	61951	92586	71248	53694	114287
2028	40936	65390	92681	71393	53390	114985
2029	38352	67068	89730	71564	53086	115704
2030	37658	69247	88575	71724	52783	116413
Mean	38352	59286	88821	71014	54003	113551

*The initial year.

the predicted consumption values of cattle and sheep meat exhibit an upward trend along with the expected values of per capita income.

Nevertheless, there is a negative correlation between the forecasted consumption values of goat meat and the expected income per capital.

Forecasting the production of meat

Table 3 presents the results of the stationarity test, indicating that the three series, namely cattle meat production (CMP), goat meat production (GMP), and sheep meat production (SMP), exhibit stationarity in the first difference. It is recommended to use the $VAR(p)$ model as described in Equation 5 for the analysis of the vector of first difference data denoted by $\Delta(\boldsymbol{MP})_t = (\Delta(CMP)_t, \Delta(GMP)_t, \Delta(SMP)_t)$`. According to the results shown in Table 9 of the R program output, it is seen that the suitable number of P lags is $p = 1$ when considering a non-intercept model, and $p = 3$ while considering a model with a trend and an intercept.

Additionally, Table 9 presents several statistical indicators for the purpose of selecting a better model between the two, using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). According to the findings presented in Table 9, the AIC criteria and BIC values indicate that the minimum values are 1912.4 and 1960.8, respectively. These values correspond to $p\ lags = 3$, suggesting that the $VAR(3)$ model, which includes both trend and intercept, is appropriate for forecasting purposes. Additionally, the chi-square statistic associated with this model $(\chi^2 = 53.158)$, and the computed p-value $(p.value = pr(\chi^2_{30} > 53.158) = 0.006)$ are also noteworthy. The p-value is found to be less than the significance level (T = 0.05), indicating that the suggested $VAR(3)$ model is suitable for predicting the production of red meat from cattle, goats, and sheep.

The data presented in Table 10 illustrates the predicted quantity of production and the corresponding predictions for domestic consumption. Based on the results shown in Table 10, it is seen that the average annual forecasted value for cattle meat production between 2022 and 2030 is 38,352 tons. This quantity is expected to account for about 54% of the average domestic consumption over the same time. Consequently, the remaining 46% of domestic consumption is anticipated to be met via imports.

The yearly average of the predicted goat meat production values for the examined period is 59,286 tons. It is expected that this quantity would fully satisfy the average domestic consumption during the stated time, hence leaving a surplus of 10% that may be allocated for exportation. In relation to the production of sheep meat, it is seen that the average annual forecasted value for the period from 2022 to 2030 is 88,821 tons. This quantity will be expected to account for 78.2% of the average domestic consumption during the same time. Consequently, the remaining 21.8% may be fulfilled via imports.

DISCUSSION

Based on the preceding analysis of the results pertaining to the estimation of domestic consumption and prediction, it appears that income per capita has a statistically significant positive impact on the domestic consumption of sheep meat. Conversely, it was discovered to have a n-significant negative effect on the domestic consumption of goat meat, as well as a non-significant positive effect on the domestic consumption of cattle meat. These findings align with economic reasoning, as an increase in income per capita tends to incentivize households to consume larger quantities of their preferred meat variety (sheep), relative to the other two options (goat and cattle). Conversely, Saudi Arabia is seeing a growing need for sheep and goat meat, with cattle following suit in terms of demand.

Conclusion

The objective of the research forecast the levels of domestic consumption and production of red meat, namely cattle, goats, and sheep, within the timeframe of 2022 to 2030.The research used secondary data ranging as a set of time series data, specifically focusing on consumption and production trends for three different types of meat as well as per capita income. The findings of the study indicate that all of these time series exhibit stationarity when analyzed at the first difference. The use of the $VARX(p)$ model, including income per capita as an exogenous variable, is proposed as an instrument to forecast the domestic consumption of meat across the three categories. Based on the minimal values of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), the most suitable model for forecasting consumption was determined to be a Vector Autoregressive model with exogenous variables $VARX(1)$ of order 1, without an intercept term and a trend component.

The findings of the estimate indicate that there is a statistically significant positive relationship between income per capita and sheep meat consumption. However, no statistically significant relationship was found between income per capita and the consumption of cattle and goats. The observed rise in domestic sheep meat consumption over the previous year has a significant negative impact on the corresponding increase in sheep meat consumption during the present year. However, this increase does not have a statistically significant effect on the consumption of either cattle or goat meat. Moreover, there is a noteworthy inverse relationship between the rise in domestic consumption of cattle in the previous year and the growth in consumption of cattle in the present year.

However, this relationship does not hold true for the consumption of sheep and goat meat, since the increase in domestic consumption of cattle does not have a statistically significant impact on the consumption of these other forms of meat. Regarding the extent of growth in domestic goat meat consumption over the previous year, it has not had significant effects on the corresponding growth in consumption of the same meat type, as well as the two other kinds (sheep and cattle). The empirical $VARX(1)$ model has successfully through a majority of diagnostic tests pertaining to the analysis of model residuals. Consequently, this research has placed reliance on the stated model to make predictions about the domestic consumption of the three distinct categories of meat.

Recommendations

Based on the analysis of the findings, the study proposes the following recommendations:

1. It is recommended that Saudi Arabia implement a program aimed at incentivizing the enhancement of red meat productivity in order to meet the growing demand for consumption.
2. Considering the significant demand for sheep meat in comparison to the other two types, the study suggests expanding local production of sheep meat.
3. It is recommended that efforts be made to promote rational consumption practices within Saudi society, with the aim of minimizing red meat wastage.

CONFLICT INTERESTS

The authors declare no conflicts of interest.

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Appendix 1

years	*Production quantity of meat in tons			*Consumption quantity of meat in tons			**Income per capita in SR
	Cattel	**Goat**	**Sheep**	**Cattel**	**Goat**	**Sheep**	
1986	25207	16868	59772	68827	16868	77288	25764
1987	18000	16758	62372	56266	16758	80676	24447
1988	24000	14700	67827	48646	14700	80995	23973
1989	25000	15113	69917	39552	15113	85176	24658
1990	28000	22900	59773	60067	22900	82232	28966
1991	27000	22587	56434	72888	23648	85907	31001
1992	28000	23500	60300	38249	22747	94057	30635
1993	29000	24000	61100	36449	23824	92692	28822
1994	30000	25000	63500	41337	24525	100945	28598
1995	26000	23800	63736	38582	23407	111623	29599
1996	18000	22400	65543	57591	22344	110271	31977
1997	16000	21000	70000	21647	27153	114567	32646
1998	20520	20000	69000	29237	27917	113390	28217
1999	21470	21000	76630	22560	29800	116500	30344
2000	21600	22200	76000	26672	24110	131041	34707
2001	21640	22400	76000	24079	23059	118955	32914
2002	21870	22300	74000	23993	22943	118174	33079
2003	22275	22400	76000	36011	23430	128682	36747
2004	22180	23700	78000	37319	26294	122090	43002
2005	22400	24100	81400	48730	25201	139180	52756
2006	24000	21300	79200	53166	23357	124980	58515
2007	29000	23500	77600	46657	25452	132185	62500
2008	29000	18100	70000	38940	21276	129943	75590
2009	42100	18400	64000	51177	19966	109847	60355
2010	44000	20300	78000	61017	23492	132460	71863
2011	43600	29000	96000	63083	31274	141438	88706
2012	51000	29000	98000	73351	32935	143519	94531
2013	52000	30160	100000	82265	36303	144291	95300
2014	38000	29992	84605	64767	36070	134833	94553
2015	41000	29851	89405	75597	35411	142570	79425
2016	41000	31044	89721	60925	34516	130750	76083
2017	42000	30507	90973	73684	34704	130976	79177
2018	42000	30224	91518	67307	33501	121146	91644
2019	43000	31377	91433	61588	35746	111001	88069
2020	42000	52189	91299	65627	56628	109537	75332
2021	40000	52861	90578	72181	55467	110207	91636

*Source of data: from FAO.
*Source of data: from General Authority for Statistics.