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Influence of national income, population, and waste emissions on food security utilization: New evidence related to Saudi Arabia's obesity

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Abstract: The prevalence of obesity in Saudi Arabia has been steadily increasing. This study aims to investigate the effects of urban population, national income, and waste emission shocks on obesity prevalence in Saudi Arabia. It utilizes annual time series data and applies the vector autoregressive (VAR) model, along with diagnostic tests including Granger causality, impulse response functions (IRFs), and forecast error variance decompositions (FEVDs). The results confirm that urban population and national income are the primary drivers of obesity prevalence in Saudi Arabia. Granger causality was observed between obesity, urban population, and waste emissions. The cumulative effects of shocks to the urban population, national income, and waste emissions significantly influence variations in obesity prevalence over time. The forecast error variance of obesity can be attributed mainly to urban population shocks. Policymakers should prioritize integrated urban planning, economic, and environmental strategies that promote healthy lifestyles, reduce socioeconomic disparities, and ensure sustainable living conditions. Coordinated efforts among public health, urban development, and economic sectors are essential to address obesity and its underlying determinants.
Keywords: *Forecasting, National income, Population, VAR.*

1. Introduction

Considering the recent focus on global food security, several developments and initiatives have been implemented that aim to enhance the pillars of food security, particularly food utilization [1, 2]. According to the FAO [1], concerning food utilization, obesity is prevalent and increasing globally. Indeed, the global prevalence of obesity has reached alarming levels, posing one of the major public health challenges and having negative economic consequences. As of 2022, the World Health Organization [3] reported that 43% of individuals aged 18 years and older were classified as overweight, while 16% were categorized as living with obesity. By 2035, it is predicted that one in four individuals (nearly two billion) will suffer from obesity if support, prevention, and treatment programs are not improved [3]. In Saudi Arabia, the results of the National Health Survey showed that the prevalence of obesity among adults (15 years and above) was approximately 23.7%, with no significant difference between males and females [4].

Obesity is characterized by excessive body fat accumulation, with a Body Mass Index (BMI) greater than or equal to 30 kg/m^2 [5]. Although BMI does not account for individual factors such as muscle mass and body composition, it is a simple tool that estimates body fat based on height and weight. Increased BMI is a major risk factor for numerous chronic complications, such as cardiovascular diseases, diabetes, musculoskeletal disorders, mental illness, and some types of cancer, including breast, ovarian, prostate, liver, and colon [6]. Beyond significant morbidity and mortality, these conditions require ongoing pharmacological treatment and specialist management [7]. In 2019, 4.3% of health

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expenditures, equivalent to 0.1% of the gross domestic product (GDP), were allocated to managing complications associated with excess weight in Saudi Arabia [8].

The obesity pandemic is considered a multifactorial disease with genetic, personal, social, and environmental influences, along with an emphasis on a sustained imbalance between energy intake and expenditure [9]. Such behaviors are related to the increased consumption of processed foods, sugary drinks, and unhealthy fats, which contribute to excess calorie intake. Sedentary lifestyles, coupled with reduced physical activity expenditure, create an energy imbalance leading to weight gain and obesity. While unhealthy dietary choices and physical inactivity play a crucial role in excess weight, emerging evidence also suggests that environmental and economic shocks act as strong drivers of obesity rates.

In high-income countries, obesity prevalence is particularly notable among disadvantaged groups, tending to be higher among lower and middle socioeconomic groups [10]. Regarding Saudi Arabia, economic development and increased prosperity have led to changes in dietary patterns and a shift towards more inactive occupations. Furthermore, urban areas in Saudi Arabia are usually highly populated, with insufficient infrastructure to support physical activity; for example, parks, sidewalks, and recreational facilities are limited. The total economic cost as a percentage of the GDP of obesity in Saudi Arabia was 2.44% in 2019 [11].

Limited access to safe and attractive spaces for exercise can discourage individuals from engaging in physical activities. Despite the Saudi government recognizing the severity of the issue and implementing various initiatives to address obesity, including awareness campaigns promoting physical activity and encouraging healthier dietary choices [12, 13], obesity levels remain severe due to several crucial factors.

The trends of obesity prevalence and urban population in Saudi Arabia show a consistent increase over time, whereas the national income trend exhibits fluctuations (Figure 1).

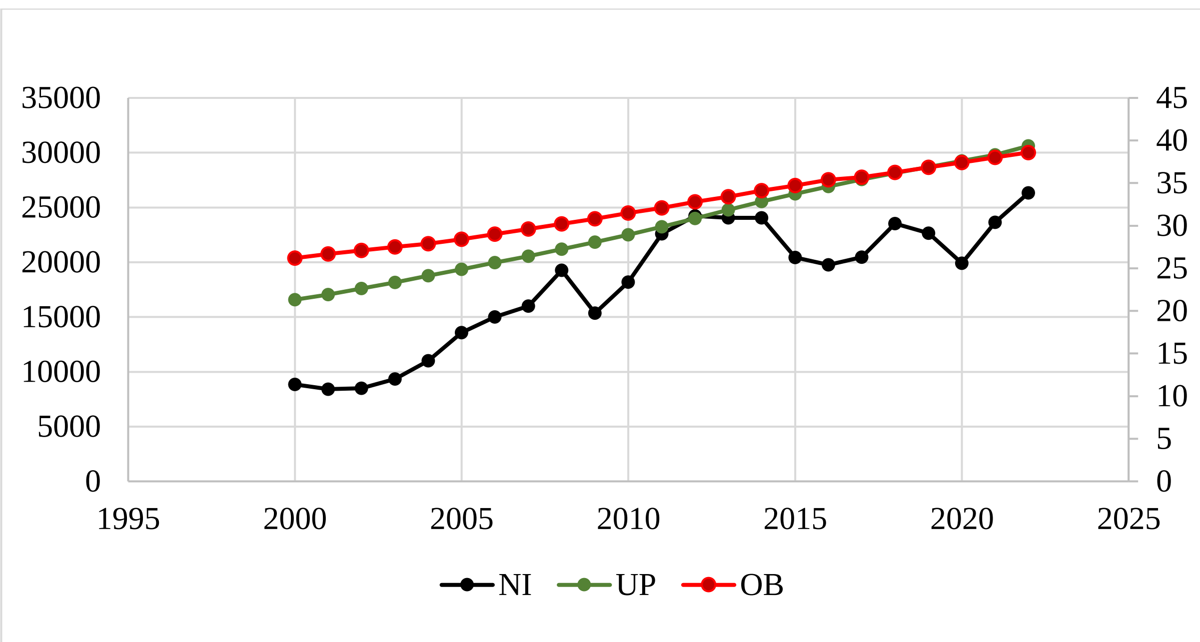

Figure 1.
National income, urban population, and obesity trends in Saudi Arabia (2000-2022).
Note: (1) The right axis represents the prevalence of obesity in the adult population (18 years and older), measured in % to represent obesity prevalence (OB); and (2) the left axis represents gross national income (NI), measured in US$ per capita, and urban population (UP), measured in 1000 people.
Source: FAO [14] and World health Organization [5].

Consequently, examining studies on obesity, income, population, and waste emissions is important because the findings will support valuable insights into the complicated nature of these problems. This will assist and support in guiding public health interventions, informing policy decisions, and promoting sustainable development practices that consider human health, economic, and environmental well-being. Thus, this study aims to investigate the effect of the urban population, national income, and waste emission shocks on obesity prevalence in Saudi Arabia. Moreover, the study aims to examine the direction of causality among these variables. Considering the study's objectives, two research hypotheses have been formulated: 1. Urban population, national income, and waste emission shocks significantly impact obesity prevalence in Saudi Arabia; and 2. There is a causal relationship among urban population, national income, waste emission shocks, and obesity prevalence in Saudi Arabia.

The rest of this study is organized as follows. In Section 2, prior empirical research is briefly reviewed. Section 3 describes the data analysis and empirical methodology used for estimation. Next, Section 4 presents the study's empirical results and discussion. Finally, Section 5 concludes with the policy implications derived from the findings.

1.1. Review

Environmental shocks such as droughts, floods, and climate change disrupt agricultural production, and environmental pollution (e.g., waste) can indirectly impact food security [15]. For instance, droughts or water scarcity can lead to crop failures, increase food prices, and reduce access to healthy dietary choices such as fruits and vegetables [16]. This, in turn, can push individuals towards cheaper, calorie-dense, and processed foods, contributing to excess weight.

When measuring food security, the dimensions of food utilization are rarely captured [17]. One study that aimed to identify the association between the levels of food utilization, food availability, economic access, and physical access to food in developing countries using factorial, correlation, and cluster assessments found that the dimensions of food security are strongly and positively correlated, with economic access having a strong association with food utilization [18]. Furthermore, Calloway et al. [2] performed a study to develop measures of food availability, utilization, and stability that can be used to complement the Household Food Security Survey Module (HFSSM). They applied Spearman's correlation coefficients, indicating that some measures were significantly related to worse health and dietary outcomes.

A growing body of evidence suggests a complex interplay between global warming and the obesity epidemic. A systematic review constructed a conceptual model elucidating this relationship and suggested that the fossil fuel economy, population growth, and industrialization drive land-use change, urbanization, and unsustainable agricultural practices [19]. These factors lead in turn to excess greenhouse gas emissions, contributing to global warming. Simultaneously, they promote motorized transportation and facilitate a nutritional transition characterized by calorie-dense, processed foods. These factors, coupled with physical inactivity, contribute to an increasing obesity epidemic. Moreover, the review indicated that climate change could disrupt food supply chains, cause food price shocks, and potentially affect nutritional intake. Additionally, rising temperatures might decrease adaptive thermogenesis, further promoting weight gain. On a universal measure, regardless of notable advancement in emission efficiency, no discernible reduction was observed [20].

In addition, during economic crises, individuals might prioritize affordability over nutritional value, selecting cheaper, processed foods with higher calories [21]. This shift contributes to increased caloric intake and potential weight gain. A study by Fox et al. [22] investigated the drivers of global increases in BMI using a two-way fixed-effects ordinary least squares (OLS) analysis to examine the influence of economic globalization, domestic economic development, and associated modernization processes on mean BMI trends. The study findings revealed that domestic factors associated with modernization, including increasing GDP per capita, urbanization, and women's empowerment, were significantly associated with rising BMI. Notably, there was a curvilinear relationship between GDP per capita and BMI, with economic growth predicting higher BMI in low-income countries but lower BMI in high-income countries. Conversely, economic globalization (measured using dependency/world systems theory) did not significantly impact BMI, and cultural globalization had mixed effects.

Another study employed a Bayesian hierarchical modeling approach to analyze data from 147 countries, incorporating five key dimensions of the macro-environment: globalization orientation; demographics; economic environment; labor market characteristics; and health policy strength [23]. The study findings revealed a non-linear relationship between income and obesity, with prevalence increasing at a declining rate as GDP per capita rose across countries. The mean income elasticity estimates were 1.23 (credible interval: 1.04-1.42) for males and 1.01 (0.82-1.18) for females. Additionally, it was found that elasticities had a negative correlation with agricultural GDP share and urbanization and a positive correlation with political globalization.

El-Sahli [24] applied a dynamic panel model with a GMM (generalized method of moments) to investigate obesity in GCC countries and found a positive and significant effect of social and economic globalization on obesity rates in GCC countries. A study conducted in the Gulf countries applied a fixed and random effects approach, which indicated that food price inflation had no significant effect on the prevalence of obesity as a factor of food utilization [25]. Most studies have focused on employing the vector autoregressive (VAR) model to evaluate food security concerning climate change and population growth. For instance, one study examined the relationship between climate variables, population growth, and food security, indicating that climate variables also play a crucial role, as rising temperatures adversely impact food security [26]. Another study examined the impacts of international collaborative efforts toward climate-friendly agricultural technologies on global food security, using the VAR model, and found that international collaborative efforts toward climate-friendly agricultural technologies decrease global food prices [27].

In conclusion, the review indicates that previous studies have demonstrated that social and economic globalization can influence obesity rates in specific regions. While many studies have examined the relationship between various factors and obesity rates, there remains a need for further studies to track changes over time to better understand the causal relationships between environmental shocks, economic factors, population, and obesity trends. Therefore, this study aims to fill this gap by exploring the complex interaction between these factors and their impact on an individual's weight; the resulting insights will be crucial for implementing multi-pronged strategies and developing effective interventions and policies to promote healthy weight and prevent obesity.

2. Materials and Methods

The FAO officially estimates food security for every country and identifies obesity prevalence as a component of food utilization. Saudi Arabia was selected as a case study among the GCC countries because it has a reported obesity prevalence that is greater than the global average [9]. The prevalence of obesity in Saudi Arabia renders it a significant topic and heightens the importance of understanding the external factors contributing to it [28]. To determine the impact of economic, demographic, and environmental shocks on Saudi obesity and investigate the existing connection and direction between these variables, we selected data on the obesity prevalence (OB) in the adult population (18 years and older), measured in %, to represent food security utilization. Similarly, we collected data on gross national income (NI), measured in US$ per capita, urban population (UP) measured in 1,000 persons, and waste emissions (WE) per capita measured in t/cap to represent the economic, demographic, and environmental factors, respectively. The annual time series data set covers the period from 2000 to 2022, retrieved from the FAO [14] and the WHO [29] was adopted for this study. The sample period is limited by data availability for food security observations.

Table 1.
Variables comparison and test of data normality.

Description of Variable	OB Obesity prevalence [a &b]	UP Urban population [a]	NI Gross national income [a]	WE Waste emissions [a]
Measuring unit	%	1000 person	US$ per capita	measured in t/cap
Mean	32.185	23405.43	18051.85	0.810
Median	32.100	23240.40	19770.68	0.840
Maximum	38.602	30621.11	26338.45	0.955
Minimum	26.200	16579.83	8417.615	0.640
Std. Dev.	3.961	4452.814	5786.983	0.091
Skewness	0.053	0.041	-0.455	-0.145
Kurtosis	1.684	1.697	1.888	1.894
Jarque-Bera	1.670	1.635	1.977	1.254
Probability	0.434	0.442	0.372	0.534
Observations	23	23	23	23

Source: FAO [14][a]; World health Organization [5][b] and authors' calculations (2024).

We observed that the data series consistently maintains mean values that fall within the range of its maximum and minimum values, indicating a strong level of consistency (Table 1). Adding the skewness, kurtosis, and Jarque-Bera's test results of the selected variables reveals that the variables are normally distributed; however, transferring data to log form aids in the validation and verification of study findings. Log forms were used for UP and NI variables, as these variables show large standard deviations.

Table 2.
Correlation and multivariate test.

Variable	OB	UP	NI	WE
OB	1.00			
UP	0.999 (0.00) ***	1.00		
NI	0.877 (0.00) ***	0.877 (0.00) ***	1.000	
WE	0.980 (0.00) ***	0.980 (0.00) ***	0.905 (0.00) ***	1.0000
Multivariate test compound symmetric			Statistical test	
Means (Hotelling's test)			F(3,20) = 85147.05 (0.00) ***	
Covariance matrix (adjusted LR)			chi²(6) = 244.48 (0.00) ***	
The correlation matrix is compound symmetric (Lawley)			chi²(5) = 45.47 (0.00) ***	
Normality (Doornik-Hansen test)			chi²(8) = 8.626 (0.3748)	

Note: The values in brackets represent the P-value, *** indicates statistical significance at 1%.

The results of the correlation coefficient and multivariate tests are presented in Table 2. We observed a significant positive connection between the selected variables. The connection between obesity and the factors of the urban population, national income, and waste emissions is strongly significant, as verified by the high Pearson correlation coefficients. Specifically, the correlation coefficient between obesity and urban population was extremely high, at r = 0.999. Similarly, the correlation coefficient between obesity and national income is significant, with a coefficient of r = 0.877. Lastly, the correlation coefficient between obesity and waste emissions was significant and reached a value of r = 0.980. This can be justified, as higher urban population levels and increased income can be linked to shifts in lifestyle and dietary patterns, resulting in greater consumption of processed foods. The results of the compound symmetry analysis assume that the means, matrix variances, and normality of all variables are equal, and that the correlation between any two variables remains constant over time and exhibits a multivariate normal distribution. This indicates that we can make assumptions based on the stability of means, variances, and correlations, which may facilitate modeling and prediction tasks. These tests were performed in several economic nutrition studies, which confirmed the same results [30]. Therefore, the multivariate normality result of the Doornik and Hansen [31] does not reject the null hypothesis of multivariate normality, p-value (0.3748); therefore, we consider the data to be reasonably consistent with a normal distribution.

Furthermore, unit root tests are used to determine whether time series are stationary. If time series have unit roots, they are considered non-stationary; these series may exhibit stochastic or deterministic trends. In this study, we applied Phillips and Perron [32] and Ng and Perron [33] unit root tests to verify the degree of integration of the series. The factors affecting obesity prevalence have been investigated using a vector autoregression (VAR) approach to explore the short-run dynamics of the variables. The suggestion of conducting the VAR model is based on the determined Johansen and Juselius [34] cointegration test results. This approach applies two tests to determine the number of cointegration vectors and whether the cointegration vectors are significant. The trace statistics and maximum eigenvalue statistics are constructed based on the following equations:

$$(1)\ \gamma_{trace}(r) = -T \sum_{i=r+1}^{\rho} ln(1-\lambda_i)$$

$$(2)\gamma_{max-eigne}(r, r+1) = -T\ ln(1-\lambda_{i+1})$$

Where λ_i estimates characteristic, T denotes the number of observations, the γ_{trace} is trace statistics test, the H_0, r =0 against the H1 of r > 0 of and $\gamma_{max-eigne}$ is the maximum eigenvalue statistics test, the H_0, r=0, against the H_1 of r =1.

2.1. VAR and its Environment Test

To capture the impact of economic, demographic, and environmental shocks on obesity prevalence in Saudi Arabia, we adopted the VAR model first established by Sims [35], which incorporates lagged values of all variables as endogenous variables [35]. In our case, these endogenous variables are obesity prevalence, national income, urban population, and waste emissions.

The VAR model of our selected variables can be identified as follows:

$$(3)\ OB_t = C_{1t} + \beta_{11}OB_{t-1,3} + \beta_{12}LogUP_{t-1,3} + \beta_{13}LogNI_{t-1,3} + \beta_{14}WE_{t-1,3} + u_{t,1}$$

$$(4)\ LogUP_t = C_{2t} + \beta_{21}LogUP_{t-1,3} + \beta_{22}OB_{t-1,3} + \beta_{23}LogNI_{t-1,3} + \beta_{24}WE_{t-1} + u_{t,2}$$

$$(5)\ LogNI_t = C_{3t} + \beta_{31}LogNI_{t-1,3} + \beta_{32}LogUP_{t-1,3} + \beta_{33}OB_{t-1,3} + \beta_{34}WE_{t-1,3} + u_{t,3}$$

$$(6)\ WE_t = C_{4t} + \beta_{41}WE_{t-1,3} + \beta_{42}LogUP_{t-1,3} + \beta_{43}LogNI_{t-1,3} + \beta_{44}OB_{t-1,3} + u_{t,4}$$

To determine the appropriate lag length model, we utilized lag length selection criteria[1] based on those of Ozcicek and Douglas Mcmillin [36]. We approved the model that can exhibit the lowest Akaike Information Criterion (AIC) or Schwartz-Bayesian Information Criterion (SBIC) value, indicating the best fit. Based on equations (3-6), to estimate the VAR order ρ, we employed equation-wise ordinary least squares (OLS) with the inclusion of two lags in this study.

By investigating VAR, we can evaluate the impact of external shocks and policy interventions, such as variations in the urban population, national income, and waste emissions, on Saudi obesity prevalence. We can quantify and understand the magnitude of these shocks, and help support policy formulation and decision-making, providing a clear and robust picture of our findings by checking the VAR diagnosis and its diagnosis of famous tests such as Granger causality, IRFs, and FEVDs tests.

2.2. Granger Causality Test

The current study applies the pairwise Granger causality test recommended by Engle and Granger [37] for detecting the direction of causality among the selected variables within a VAR framework. The pairwise Granger causality model can be written as:

[1]These criteria involve the Akaike Information Criterion (AIC), Schwartz-Bayesian (SBIC) criterion, Hannan-Quinn (HQIC) criteria, Likelihood Ratio, sequential modified (LR) criteria, and Final Prediction Error (FPE).

$$(7) OB_t = \emptyset_1 + \sum_{j=1}^{n} \emptyset_{1j} EDE_{t-1} + \sum_{j=1}^{n} \emptyset_{2j} OB_{t-j} + \omega_{1t}$$

$$(8) EDE_t = \delta_1 + \sum_{j=1}^{m} \delta_{1_j} \mathrm{OB}_{t-1} + \sum_{j=1}^{m} \delta_{2_i} EDE_{t-j} + \omega_{2t}$$

Where EDE are economic, demographic, and environmental factors, which could be national income (Log NI), urban population (log UP), or waste emissions (WE), respectively. $\emptyset$ and δ are intercepts of the equations, and their corresponding j stands for the coefficients of the equations; n, and m represent the lag order, and $\omega_{it}(i = 1\ to\ 16)$ are uncorrelated error terms for the equations.

2.3. Impulse Response Functions and Variance Decomposition Tests

Finally, we examined IRFs and FEVDs to explore the relationship between obesity prevalence and its determining factors, aiming to investigate the source of shocks. We used these analytical approaches because they provided insights into the dynamic properties of the system and allowed for the examination of the progress of variable shock innovations and the way in which the OB, UP, IN, and WE variables affect each other beyond the sample period within the context of the VAR model. Furthermore, our study applies the Cholesky innovations, which provide insights into innovations that have positive or negative impacts and whether these impacts are short- or long-term [35]. As the IRFs do not calculate the magnitude of these impacts [38], we assessed the magnitude of the innovation shocks of the selected variables using the FEVD method [38]. This test splits the variation in an endogenous variable into the factor shocks to the VAR system. In addition, the FEVDs determine the percentage contribution of each innovation to the FEVDs of the dependent variable at a specific time horizon. We follow Charfeddine and Kahia [39] and Vo and Vo [40] to extend the horizon up to 10 years for both ERFs and FEVDs.

3. Results and Discussion

This section presents the findings and discussion relating to the highlighted objectives of the study.

3.1. Preliminary Test Results

Summary results of Phillips-Perron and Ng-Perron unit root tests are displayed in Table 3. Based on the results of the P-P unit root tests, it appears that the studied variables (OB, LogUP, LogNI, and WE) exhibit evidence of non-stationarity, as the test statistics Z(rho) and Z(t) do not exceed the corresponding critical values at any significance level. Non-stationarity implies that these variables have a unit root, indicating a long-term trend or dependence on past values. However, based on the signs of the test statistics of the Ng-Perron unit root test, proposed by Ng and Perron [33], negative values for MZa, MZt, MSB, and MPT generally suggest evidence against a unit root and support stationarity. Therefore, it can be inferred that the variables OB, LogUP, LogNI, and WE show some evidence of stationarity, based on the Ng-Perron test results.

Table 3.
Unit root results

Phillips-Perron (PP) Statistics (Drift+ Trend Model)					
Variable		**OB**	**LogUP**	**LogNI**	**WE**
Test statistic	Z(rho)	- 6.317	1.233	-4.897	-11.864
	Z(t)	-2.518	0.749	-1.560	-2.705

Note: Dickey–Fuller critical values at 1% = -22.500, at 5% = -17.900 and at 10% = -15.600 for Z(rho). Dickey–Fuller critical values at 1% = -4.380, at 5% = -3.600 and at 10% = -3.240 for Z(t).

Table 3.
Continue…

Ng-Perron test statistics (Drift+ Trend Model)				
Test	**MZa**	**MZt**	**MSB**	**MPT**
Variable				
OB (0)	-2.626	-1.143	0.435	34.589
LogUP (3)	-4.997	-1.329	0.266	16.957
Log NI (0)	-4.179	-1.422	0.340	21.558
WE (0)	-6.414	-1.790	0.279	14.207

Postestimation test results

Test	**Chi²**	**Prob > chi2**	**Decision**
Breusch–Godfrey LM test for autocorrelation	0.424	0.515	No serial correlation
Durbin's alternative test for autocorrelation	0.325	0.569	No serial correlation
LM test for autoregressive conditional heteroskedasticity (ARCH)	1.319	0.251	no ARCH effects

Durbin–Watson d-statistic (4, 20) = 1.332
Authors' calculations (2024).

Note: At 1% asymptotic critical values = -23.800, -3.4200, 0.143, and 4.03000 for MZa, MZt, MSB, and MPT, respectively.
At 5 % asymptotic critical values = -17.300, -2.9100, 0.168, and 5.48000 for MZa, MZt, MSB, and MPT, respectively.
At 5 % asymptotic critical values = -14.200, -2.620, 0.185, and 6.670 for MZa, MZt, MSB, and MPT, respectively.
- Numbers in parentheses are the length of the augmented lags involved in the unit root test.
The total number of observations is 23.

Moreover, based on the test results provided in Table 3, there is no strong evidence of autocorrelation and conditional heteroskedasticity in the data, as the test statistics are relatively small; also, their p-values are high (Chi2 = 0.424 and 0.325 with corresponding p-values = 0.5149 and 0.5686 for Breusch–Godfrey LM test and Durbin's alternative test, respectively). The absence of autocorrelation and serial correlation implies that the observations are independent and unlinked to each other. Similarly, no autoregressive conditional heteroskedasticity (ARCH) was observed among the variables, which confirms that the conditional variance of the data is constant.

Table 4.
Optimal lag selection.

Lag	**LL**	**LR**	**df**	**p-value**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	115.834				2.8e-10	-10.651	-10.608	-10.452
1	247.913	264.160	16	0.00	4.6e-15	-21.706	-21.4901	-20.711
2	274.317	52.808*	16	0.00	2.1e-15*	-22.697*	-22.308*	-20.906*

Note: * Optimal lag, Endogenous: OB, logUP, logNI, and WE, Exogenous: Constant.
LL stands for the log-likelihood, LR represents the likelihood ratio test statistic, FPE stands for the Final Prediction Error, and AIC stands for Akaike Information Criterion. HQIC stands for Hannan-Quinn Information Criterion, and SBIC stands for Schwarz Bayesian Information Criterion.

As can be seen in Table 4, the model with a lag order of 2 has a significantly better fit compared to those with lag orders of 1 and 0. This indicates higher log-likelihood values, lower AIC, HQIC, and SBIC values, as well as a significant improvement in model fit, according to the likelihood ratio tests (LR) and the small p-values. Accordingly, we adopted the results of the VAR model with 2 lags.

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Table 5.
Johansen's cointegration results.

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized		**Trace**	**0.05**	**Prob.****
[a]No. of CE(s)	**Eigenvalue**	**Statistic**	**Critical Value**	**Critical Value**
None *	0.932	113.346	55.246	0.000
At most 1 *	0.744	57.031	35.010901	0.000
At most 2 *	0.575	28.380	18.398	0.001
At most 3 *	0.391	10.402	3.841	0.001
Unrestricted Cointegration Rank Test (Max-eigenvalue)				
Hypothesized		Max-Eigen	0.05	Prob.**
[a]No. of CE(s)	Eigenvalue	Statistic	Critical Value	Critical Value
None *	0.932	56.316	30.815	0.000
At most 1 *	0.744	28.651	24.252	0.012
At most 2 *	0.575	17.978	17.148	0.038
At most 3 *	0.391	10.402	3.841	0.001

Note: [a]No. of CE(s): This column shows the number of cointegrating relationships being tested. CE stands for cointegrating equations.
* Denotes rejection of the hypothesis at the 0.05 level.
**MacKinnon et al. [41] p-values.

The Trace and the Max-eigenvalue tests were used to examine the unrestricted cointegration rank test [42]. Both tests involve comparing the eigenvalues (characteristic values) of a matrix derived from the data to critical values to determine the number of cointegrating relationships. Our results, shown in Table 5, confirm that the null hypothesis of all equations is rejected since the test statistic exceeds the critical value with a probability (p-value) less than 0.05. Also, referring to the results of the Trace test and the Max-eigenvalue tests attained from Table 5, there is clear evidence of the presence of cointegrating relationships among the selected variables. This outcome confirms the application of the VAR approach to investigate the connection between the selected variables.

3.2. VAR Results

According to the lag order selection test, the results for lag-2 in the VAR analysis were examined and approved. From Table 6, a significant positive relationship exists in OB itself; this suggests that a one-unit increase in OB-2 leads to a 0.394-unit increase in OB at the current period (t) while holding other variables constant (at $p < 0.05$). A significant positive effect of LogUP (-2) results in a 59.541-unit increase in OB (at $p < 0.01$). This may be attributed to a sedentary lifestyle and greater availability of fast-food chains in urban areas; also, urban living can relate to higher levels of stress due to factors such as noise pollution and overcrowding, which positively influence obesity prevalence. Several scholars have confirmed similar results, indicating that obesity has increased in urban populations [43-45]. Therefore, careful consideration of the relationship between urbanization and obesity can guide the development of inclusive urban health policies that encourage healthy behaviors, generate supportive environments for physical activity, and address complex factors contributing to obesity in urban settings. By applying evidence-based interventions, communities can work towards reducing obesity rates and improving the overall health and well-being of their populations.

Additionally, a significant positive effect of LogIN (-2) and LogNI (-2) on the OB in the short run was observed (i.e., one unit increase in LogIN (-2) and LogNI (-2), indicating increases in OB by 59.541 and 1.152, respectively, at $p < 0.05$). However, WE-2 does not affect OB. The outcomes imply that prevailing obesity rates, national income, and waste emissions have no significant impact on the urban population. Furthermore, it was observed that OB and WE are not statistically significant in relation to national income. However, WE (-1) marginally significantly influences national income at the 10% significance level ($\beta = 1.320$, $P > z = 0.08$). These results confirm that previous waste emissions (WE-1 and WE-2) have the most significant impact on current waste emissions (WE). The urban population (LogUP-1 and LogUP-2) also plays a significant role, with positive and negative impacts on WE. Additionally, national income (LogIN-2) is positively significant to WE, while OB does not exhibit statistically significant relationships with waste emissions. In their study, Magazzino et al. [46] found that income level and urban population are negatively related to greenhouse gas (GHG) emissions from the waste sector [46].

Table 6.
VAR results.

Equation (3) OB					Equation (4) Log UP				
Predictor variable	**β**	**S. E**	**z**	**P>z**	**Predictor variables**	**β**	**S. E**	**z**	**P>z**
OB (-1)	0.352	0.149	2.369	0.02**	OB (-1)	0.003	0.002	1.389	0.16
OB (-2)	0.394	0.150	2.620	0.01**	OB (-2)	-0.000	0.002	-0.063	0.95
LogUP(-1)	-53.985	18.289	-2.952	0.00***	LogUP(-1)	1.706	0.242	7.047	0.00***
LogUP (-2)	59.541	19.233	3.096	0.00***	LogUP (-2)	-0.843	0.255	-3.311	0.00***
LogIN (-1)	0.337	0.312	1.080	0.28	LogIN (-1)	0.010	0.004	2.535	0.01***
LogNI-2)	1.152	0.282	4.077	0.00***	LogNI-2)	-0.004	0.004	-0.953	0.34
WE (-1)	4.204	0.984	4.274	0.00***	WE (-1)	0.016	0.013	1.218	0.22
WE (-2)	-1.093	0.915	-1.194	0.23	WE (-2)	-0.016	0.012	-1.358	0.17
cons	-23.380	13.259	-1.763	0.08*	cons	0.486	0.176	2.768	0.01***
RMSE	0.065				RMSE	0.001			
R-sq	0.999				R-sq	0.999			
X2	112125.1***				X2	270836.8 ***			
Equation (5) logNI					**Equation (6) WE**				
Predictor variables	β	S. E	z	P>z	Predictor variables	β	S. E	z	P>z
OB (-1)	-0.100	0.116	-0.866	0.39	OB (-1)	0.029	0.030	0.967	0.33
OB (-2)	-0.062	0.117	-0.527	0.60	OB (-2)	-0.012	0.030	-0.408	0.68
LogUP(-1)	4.998	14.220	0.352	0.73	LogUP(-1)	8.286	3.631	2.282	0.02**
LogUP (-2)	2.598	14.954	0.174	0.86	LogUP (-2)	-7.859	3.819	-2.058	0.04**
LogIN (-1)	0.354	0.243	1.461	0.14	LogIN (-1)	-0.000	0.062	-0.005	1.00***
LogNI-2)	-0.232	0.220	-1.055	0.29	LogNI-2)	-0.074	0.056	-1.312	0.19
WE (-1)	1.320	0.765	1.725	0.08*	WE (-1)	0.797	0.195	4.082	0.00***
WE (-2)	-0.059	0.712	-0.083	0.93	WE (-2)	-0.670	0.182	-3.688	0.00***
cons	-25.229	10.309	-2.447	0.01***	cons	-1.467	2.633	-0.557	0.58
RMSE	0.051				RMSE	0.013			
R-sq	0.922				R-sq	0.985			
X2	247.473 ***				X2	1357.535***			

Note: ***, **, * Levels of significance at 1%, 5% and 10%, respectively.

To conclude, lower RMSE values (less than 1) for all equations reveal improved accuracy in predicting the outcome variable. This indicates a relatively good level of accuracy of the VAR models and reflects a higher level of precision.

3.3. Causality Results

Based on the VAR model results, we focused on the Granger causality between the selected variables. With regard to the causal relationship between obesity, urban population, national income, and waste emissions, the results suggest the existence of a feedback relationship indicating the presence of interdependencies between these variables, except for urban population and waste emissions (Table 7). Granger causality supports the existence of bidirectional causality among obesity prevalence, urban population, and national income.

A unidirectional causality was observed running from waste emissions to obesity prevalence; however, no causality from the opposite direction was noted. Waste emissions have the potential to pollute soil and water reservoirs with harmful compounds, impacting agricultural yields and marine life. Such contaminated food sources may interact with toxins that interfere with bodily metabolic functions, potentially resulting in weight gain and various health complications.

Additionally, under the model's assumption, the null hypothesis of no causation from UP to WE and vice versa was observed. Our results contrast with those of Magazzino et al. [46], who confirmed a unidirectional causality running from urban population to waste emissions. This suggests that the waste emissions may be caused by other factors, such as advancements in modern technology and industry, which have a stronger influence on waste emissions than the urban population. Furthermore, no causation from waste emissions to national income or vice versa was observed. The effects of waste emissions on national income or vice versa might take a long time to manifest; alternatively, the observation period in our study may not have been sufficient to capture the causal relationship precisely.

Table 7.
Causality results.

Equation: OB			**Equation: LogUP**		
Excluded	**Chi²**	**Causality direction**	**Excluded**	**Chi²**	**Causality direction**
logUP	9.762***	Bidirectional	OB	5.658*	Bidirectional
logNI	21.28***	Bidirectional	logNI	6.539**	Bidirectional
WE	18.34***	Unidirectional	WE	2.493	No causality
ALL	68.752***	Causality	ALL	19.207***	Causality
Equation: LogNI			Equation: WE		
Excluded	Chi²	Causality direction	Excluded	Chi²	Causality direction
OB	5.6378*	Bidirectional	OB	1.4195	No causality
logUP	7.0438**	Bidirectional	logUP	6.0319**	Unidirectional
WE	3.2617	No causality	logNI	1.8362	No causality
ALL	11.97*	Causality	ALL	19.063***	Causality

Note: ***, ** and * denote significance at 1%, 5%, and 10%, respectively.

3.4. Historical Decomposition (HD)

Before examining the FEVDs, we performed the historical decomposition (HD) for obesity prevalence. This is particularly important for forecasting and understanding the range of possible outcomes of our results. HD is a technique within the VAR environment, as proposed by Kilian and Vigfusson [47]. It allows us to interpret historical fluctuations in time series data for obesity prevalence by examining the identified structural shocks. By incorporating the total stochastic shocks, the VAR model can capture the uncertainty and unpredictability in the behavior of obesity prevalence.

According to the results of the historical decomposition variation analysis, shown in Figure 2, the contribution of UP shocks to the total variation in OB began to become noticeable in 2002 (Figure 2 B). The largest variance was recorded starting in 2016, when positive total stochastic and descending shocks for UP were observed, indicating that the forecast error variance of the UP model has decreased over time. The contribution of UP shocks to the total variation in OB also started to become noticeable in 2004, with the peak occurring in 2020, when positive total stochastic and downward shocks for NI were observed (Figure 2C). The impact of WE shocks on the total variation in OB became noticeable in 2003 with negative total stochastic; the maximum variance was recorded in 2022, when positive total stochastic and increasing shocks for WE were observed (Figure 2D), indicating that the forecast error variance of the UP model has decreased over time. Overall, the evolution of various shocks (UP, NI, and WE) and their impact on the total variation observed in OB over time suggest that the forecast error variance of the UP model has decreased, indicating an improvement in its predictive accuracy.

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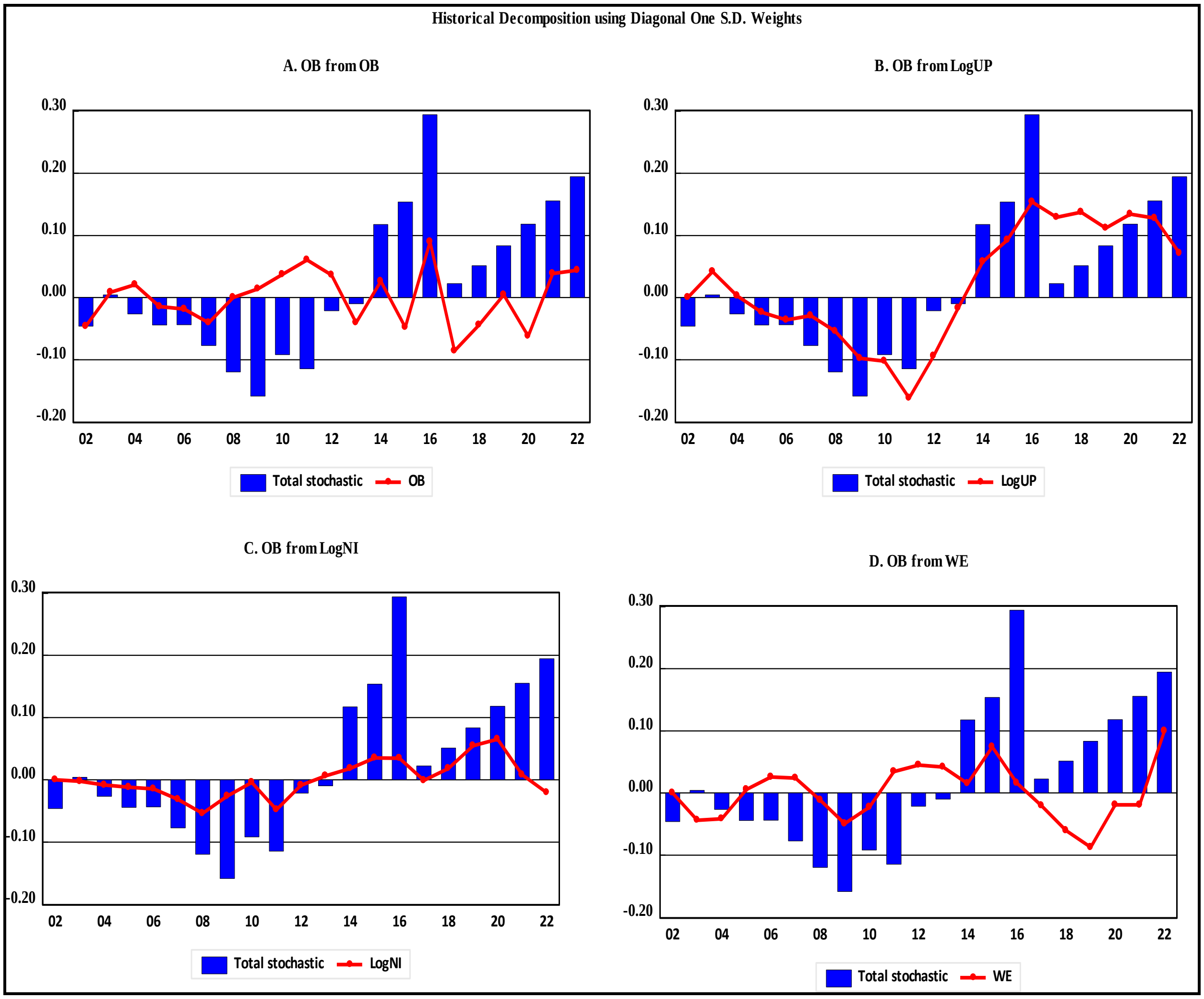

Figure 2.
Historical Decomposition.
Note: The total stochastic component represents the random or unpredictable variations in the variable beyond those that can be explained by the specified variables or known relationships. It captures the residual or unexplained variation in the variable's behavior.

3.5. Forecast Error Variance Decompositions and Impulse Response Functions Results.

Innovations shocks to an individually selected variable can affect both its own variations and variations in other variables. From the results of the FEVDs, we may conclude that in the short run (e.g., 1–4 years), variation in obesity is largely due to its own shocks, but in the long run, they become increasingly interconnected with other studied variables. For example, the variation in the obesity shock can be explained by its own shock, showing a declining rate across 10 horizons (ranging from 100% in the first year to 39% in the tenth year). The contribution of the UP to obesity variation is expanding, reaching 14.9% in year 2 and 39.16% in year 10, thus proving that a rise in urban population boosts obesity. These findings are consistent with those of Wu et al. [48] and Anza-Ramirez et al. [44]. Simultaneously, the contributions of national income and waste emissions to obesity variation fluctuate across the 10 horizons. Additionally, our analysis reveals that a higher percentage of changes in forecast errors among the urban population can be attributed to their own values. In the long run, OB and NI explain approximately 38.39% and 14.35%, respectively, of the error variation in UP in year 10, while waste emissions explain much less (i.e., 4.34%) of the forecast error variation in UP. Furthermore, obesity and urban population explain 20.37% and 42.86% of the national income of their innovations in the year 10. The share of waste emissions in national income is minimal (i.e., approximately 6.30%), and a 30.48% portion of national income is contributed by its innovative shocks.

Obesity and urban population increase innovative shocks of waste emissions by 35.72% and 26.62% in the long run. The innovative shock of waste emissions accounts for 26.72%, while 10.95% of the national income is attributed to waste emissions.

Table 8.
Forecast Error Variance Decompositions Results under A VAR System.

	Variance Decomposition of OB				**Variance Decomposition of LogUP**			
Period	OB	LogUP	LogNI	WE	OB	LogUP	LogNI	WE
1	100.000	0.0000	0.0000	0.000	19.877	80.124	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(15.368)	(15.368)	(0.000)	(0.000)
2	53.704	14.892	10.707	20.698	28.323	65.655	5.405	0.618
	(18.045)	(15.450)	(11.048)	(10.250)	(16.552)	(16.536)	(5.727)	(2.615)
3	50.398	9.003	20.658	19.944	32.152	56.004	9.5466	2.298
	(17.148)	(13.467)	(13.396)	(10.857)	(17.435)	(18.360)	(10.179)	(5.685)
4	48.630	9.126	21.568	20.676	34.482	50.410	11.429	3.649
	(16.993)	(14.045)	(14.267)	(12.255)	(17.939)	(19.635)	(12.695)	(7.805)
5	46.590	18.307	18.885	16.217	35.925	47.763	12.092	4.220
	(16.533)	(15.027)	(13.965)	(11.294)	(18.339)	(20.281)	(13.805)	(8.873)
6	43.407	28.197	16.477	11.919	36.829	46.453	12.457	4.261
	(16.424)	(15.935)	(13.602)	(10.752)	(18.646)	(20.591)	(14.290)	(9.517)
7	41.137	34.351	15.545	8.968	37.412	45.487	12.922	4.180
	(16.777)	(16.474)	(13.232)	(9.8168)	(18.891)	(20.732)	(14.482)	(9.5870)
8	40.013	36.938	15.405	7.644	37.827	44.519	13.484	4.170
	(17.043)	(16.804)	(13.427)	(10.047)	(19.018)	(20.646)	(14.558)	(9.649)
9	39.580	38.215	15.193	7.013	38.145	43.617	13.992	4.246
	(17.500)	(17.223)	(13.431)	(9.972)	(19.141)	(20.603)	(14.691)	(9.708)
10	39.433	39.164	14.892	6.5110	38.393	42.924	14.345	4.339
	(17.727)	(17.656)	(13.615)	(10.371)	(19.255)	(20.654)	(14.912)	(9.901)
	Variance Decomposition of LogNI				Variance Decomposition of WE			
Period	OB	LogUP	LogNI	WE	OB	LogUP	LogNI	WE
1	8.5183	25.319	66.163	0.000000	19.671	0.835	11.428	68.066
	(12.1750)	(14.5118)	(16.5886)	(0.00000)	(15.5505)	(6.44443)	(10.3272)	(16.1306)
2	8.476	23.052	62.596	5.876	33.526	8.307	8.343	49.824
	(12.8524)	(14.1444)	(16.3454)	(7.75240)	(17.4593)	(12.0061)	(9.32016)	(18.0859)
3	10.215	28.455	52.812	8.5183	37.289	20.928	6.406	35.377
	(13.6600)	(16.5886)	(16.8110)	(9.17174)	(16.9699)	(16.6719)	(10.1925)	(17.4174)
4	13.016	40.598	39.960	6.426	37.181	26.937	6.558	29.324
	(14.4136)	(16.7113)	(16.3378)	(8.54147)	(16.9081)	(17.2924)	(11.3259)	(16.5774)
5	15.625	47.066	31.894	5.415	36.973	26.710	8.919	27.408
	(15.4996)	(16.4320)	(15.3459)	(8.36702)	(16.6718)	(16.6677)	(12.0835)	(16.2412)
6	17.784	46.867	30.579	4.771	36.357	25.771	10.903	26.969
	(16.1569)	(16.2663)	(15.0270)	(8.69868)	(16.8617)	(16.0085)	(12.4050)	(15.9114)
7	19.045	44.536	31.174	5.245	35.946	25.362	11.247	27.446
	(16.6381)	(16.0058)	(15.0415)	(8.96344)	(17.0302)	(15.8334)	(12.6799)	(15.7512)
8	19.741	43.060	31.048	6.152	35.985	25.334	11.178	27.503
	(16.8132)	(16.0066)	(15.1116)	(9.74653)	(17.1110)	(16.1561)	(12.8629)	(15.6956)
9	20.193	42.745	30.715	6.347	35.870	25.952	11.030	27.149
	(17.1076)	(16.1856)	(15.2332)	(10.1021)	(17.1370)	(16.3456)	(13.0521)	(15.6415)
10	20.370	42.856	30.479	6.295	35.716	26.615	10.951	26.718
	(17.3057)	(16.3852)	(15.1908)	(10.3157)	(17.3677)	(16.5253)	(13.2575)	(15.7187)

Note: Cholesky One S.D. (d.f. adjusted) Innovations; Cholesky ordering: OB LogUP LogNI WE and Standard errors: Monte Carlo (1000 repetitions) standard deviations in parentheses.

Figure 3 shows the IRFs (with one standard error and a 10-year horizon) for each endogenous variable, based on the VAR system, and the years after the impulse shocks are displayed on the horizontal axis. We follow Habib [49] and Elzaki [50] for computing the IRFs to describe the reaction of one variable in the system to the innovations using the Cholesky decomposition.

During the 10 years, positive self-shocks were observed in OB and UP, while functioning self-shocks were observed in NI and WE in the 10 projected horizons. We also observed positive innovation shocks of the urban population and waste emissions on obesity prevalence in the long run; however, when considering the 3-year horizon, negative innovation shocks of the urban population and national income in the short run were observed. Our results confirm the fluctuation of innovation shocks of the urban population and national income on waste emissions. Additionally, the NI response to the innovation shocks of UP, WE, and OB was functioning in the short and long runs. The innovation shocks of OB on WE are greater in the short run compared with the long run. This suggests that OB responds symmetrically to its shocks and urban population shocks, indicating that obesity is endemic in the urban population. Similarly, Martins-Silva et al. [51] pointed out that obesity epidemics exist in both rural and urban areas. As far as national income shocks of obesity prevalence are concerned, they develop in the long run.

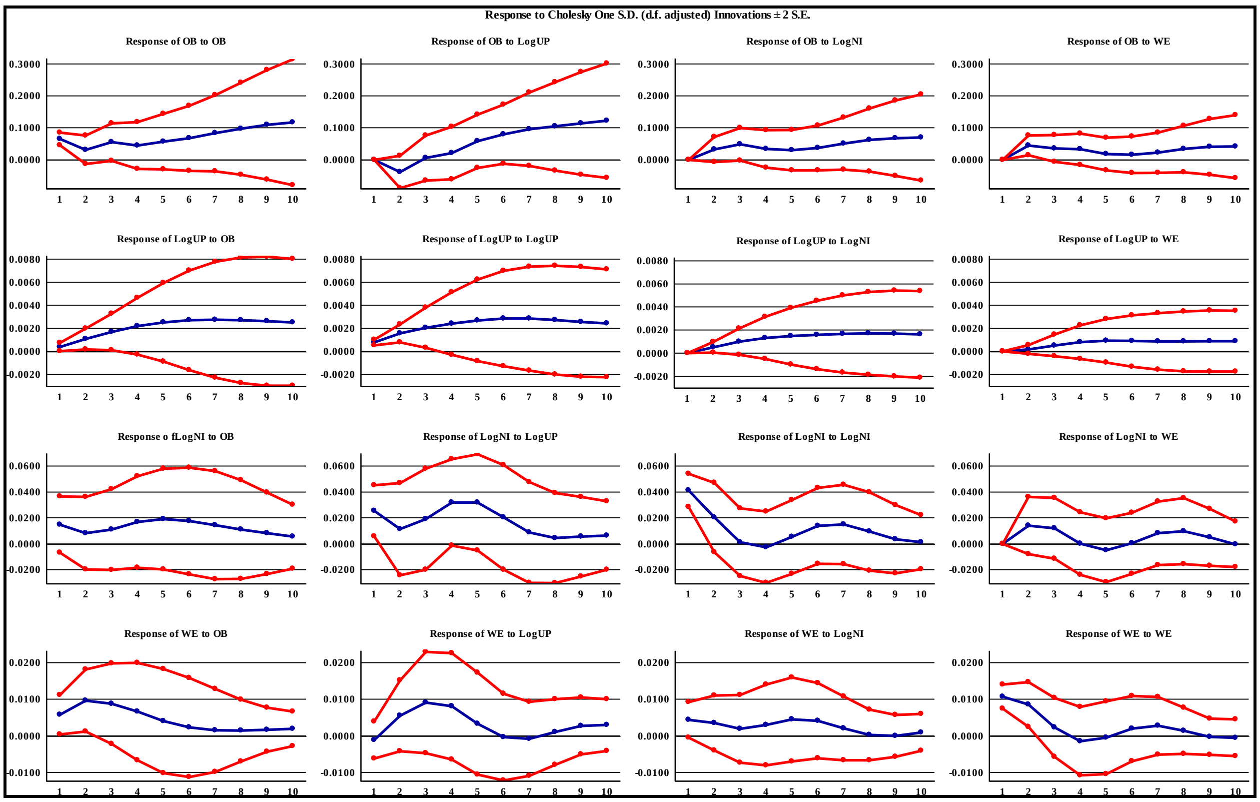

Figure 3.

Impulse response functions.

Note: The "one S.D. (d.f. adjusted) innovations" refers to the standard deviations of the innovations (or errors) in the VAR model, which are adjusted for the d.f. (degrees of freedom). The ± 2 S.E. (standard errors) represents the range around the estimated values of the Cholesky one S.D. innovations (the y-axis). The standard error bands are covered with two red lines (to construct confidence intervals). The x-axis typically represents the period of the time series. A blue middle line depicts the response of one variable to a shock of itself or another endogenous variable.

4. Conclusions

The trend of obesity prevalence in Saudi Arabia shows an increase over time. This paper investigates the effect of shocks to national income, urban population, and waste emissions on obesity prevalence in Saudi Arabia. Additionally, the study aims to examine the direction of causality among these variables. The study utilizes annual time series data covering the period 2000-2022 and applies the VAR model by checking its diagnosis through well-known tests, including IRFs and FEVDs, which enable the impact of shocks to be examined among obesity, national income, urban population, and waste emissions. The direction of causality between the studied variables was detected by applying Granger causality. Before applying the VAR model, the P-P and Ng-Perron methods were used to check the unit root status of the variables. Based on the PP unit root results, the studied variables are non-stationary. However, the Ng-Perron test provided evidence supporting stationarity.

The results have demonstrated the absence of autocorrelation, serial correlation, and autoregressive conditional heteroskedasticity among the variables. This indicates that the conditional variance of the data remains constant. Additionally, the findings provide evidence of cointegrating relationships among the selected variables. This outcome supports the use of the VAR approach with two lags to examine the relationship between the variables. The VAR results indicated that the urban population and national income are drivers of obesity prevalence in Saudi Arabia; however, no statistically significant link was found between waste emissions and obesity.

The causality tests indicated bidirectional causality between obesity prevalence and urban population, and national income. The tests revealed a unidirectional causality running from waste emissions to obesity prevalence. These findings highlight the complex interplay between various factors influencing obesity rates, emphasizing the need for holistic approaches in addressing this public health issue.

In conclusion, the HD, IRFs, and focusing results indicate that the cumulative effects of different shocks to the urban population, national income, and waste emissions play a significant role in shaping the overall variation observed in obesity prevalence over time. The FEVDs' outcomes revealed that a considerable part of the forecast error variance of OB can be attributed to UP shocks. In contrast, waste emissions reported a relatively smaller part of the forecast error variance of obesity.

Given the substantial influence of urban population shocks in explaining the variation in obesity prevalence, policymakers should prioritize urban projection strategies that promote healthy lifestyles and physical activity. Similarly, considering the substantial impact of national income shocks on obesity prevalence, policymakers should consider implementing economic policies that support socioeconomic conditions conducive to healthy living. Even though waste emissions were noticed to have a minor impact on obesity prevalence, it is important to address this issue to ensure overall public health and environmental sustainability. Overall, policymakers are recommended to encourage collaboration and coordination among appropriate sectors, including urban planning, public health, environmental agencies, and economic development, to develop comprehensive strategies that address obesity from several angles. Moreover, future research could further explore how individuals' available income or purchasing power influences the incidence of obesity.

Nevertheless, certain limitations of the study findings should be considered. We have not explicitly considered other significant factors that could hypothetically impact obesity, involving dietary habits and cultural effects, such as socioeconomic status, cultural norms, and individual lifestyle choices. Furthermore, the data employed for the analysis are restricted to the timeframe of assessing food security in Saudi Arabia, which could potentially affect the consistency and validity of our results.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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