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Organic food consumption dynamics in Germany during economic crises

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ABSTRACT

This study investigates the effects of the 2008 global economic crisis and the 2020 COVID-19 pandemic on organic food consumption in Germany, the largest organic market in Europe. Specifically, it examines (1) the relationship between Gross Domestic Product (GDP) and organic food consumption during crisis and non-crisis periods (disposable income is also employed as an alternative measure instead of GDP to verify the stability of the results), (2) the presence of a long-term equilibrium between these variables, (3) the short-term dynamics governing the adjustment toward this equilibrium, and (4) the differences in these dynamics under stable economic conditions and crisis periods. To analyze these relationships, the study employs an Error Correction Model (ECM) with Markov Regime Switching (MRS) and Threshold Cointegration Methodology (TCM), as both modeling frameworks allow for the identification of structural changes in the data. The findings indicate a significant dependence of organic food consumption on GDP (income), but only in non-crisis periods. While a long-term equilibrium relationship between GDP (income) and organic food consumption is confirmed, the adjustment mechanism toward this equilibrium varies considerably between economic stability and crisis periods.

Keywords: consumption, organic food, Markov Regime Switching (MRS) model, Error Correction Model (ECM), crisis, Germany

INTRODUCTION

Organic food consumption has gained attention due to health, environmental, and ethical concerns. Organic foods, produced without synthetic pesticides, fertilizers, or genetically modified organisms (GMOs), are perceived to have health benefits, including reduced pesticide exposure and superior nutritional quality. Organic foods promote biodiversity and soil health, enhance animal welfare, and contribute to rural development **[1]**, **[2]**, **[3]**, and **[4]**. The global organic food market has grown significantly in the past two decades, led by the US and Europe **[5]**. A steady rise in the demand for organic food products is observed worldwide, including in developing nations **[6]**. The EU has become a net organic food importer, reflecting growing domestic demand **[7]**. According to **[8]**, substantial organic food consumption is in France, especially vegetables, with women consuming more than men. High organic consumption among urban, well-situated households was found in Denmark, Great Britain, and Italy **[9]**.

Economic and political factors influencing organic food consumption are discussed by **[10]**, finding that national policies, including farmer subsidies, organic certification, and labeling systems, heavily influence the share of organic food in total consumption. Effective distribution systems, premium pricing, and soil conditions also play significant roles. Environmental concern, ethnocentrism, and trust in domestic production significantly impact consumer preferences for organic food **[11]**.

According to **[12]**, German consumers strongly prefer organic food due to health, environmental, and quality concerns. The country's well-established organic market and robust certification systems contribute to higher consumption rates. In contrast, despite similar attitudes, UK consumers do not strongly link organic food with environmental benefits. Other studies debate consumers' food-buying practices concerning sustainability **[13]**, and **[14]**, and **[15]**. European policymakers promote organic agriculture and consumption to enhance food system sustainability **[16]**, and **[17]**.

Numerous studies have established a psychological framework of consumer behavior in the organic food sector **[18]**, **[19]**, **[20]**, **[21]**, and **[22]**. Evidence shows that price perceptions do not significantly affect organic food purchases, showing strong intrinsic motivation despite higher costs **[23]**. Moreover, **[24]** emphasizes that sustainable food consumption, mainly organic, is driven by personal health benefits and broader environmental considerations.

Economic crisis in 2008 reduced food quality and quantity in developing countries due to higher prices and lower incomes **[25]**. Despite favorable attitudes, financial crisis reduced European organic food purchases **[26]**. Comparison of the impact of the 1997-98 Asian financial crisis and the 2008 global crisis on Indonesian food production is discussed by **[27]**. Economic implications of the coronavirus crisis on the food industry is analyzed in **[28]**.

Most empirical papers analyzing factors affecting consumers' choice of organic foods apply discrete choice models **[29]**, and **[30]**. Results on how consumers' income affects demand for organic food are ambiguous. The effect of various factors on consumers' choice of organic foods in Denmark by applying discrete choice models is studied in **[31]**. The results indicate that the consumer's higher income, age, and education level significantly increase the probability of being a heavy consumer of organic food.

On the other hand, **[32]** discovered that organic food consumers are not predominantly wealthy. Their analysis showed that many organic food buyers have annual incomes below $50,000, challenging the notion that only higher-income households drive the demand for organic products. Similarly, **[23]** argues that income plays a minor role compared to consumers' attitudes and beliefs.

All the cited empirical research on the organic market has focused on microeconomic cross-sectional data. Empirical literature analyzing the organic market on a macroeconomic level using time series data is practically missing. Rare exceptions are **[33]**, and **[34]**. Therefore, this study aims to extend this relatively scarce literature by analyzing organic food consumption at a macroeconomic level utilizing a time series data of aggregate indicators in Germany, Europe's largest organic market. Moreover, the paper pays particular attention to how substantial economic downturns influenced organic food consumption. Finally, the paper investigates short-run dynamics and long-run equilibrium relationships between organic food consumption and a country's economic activity level, contributing significantly to the existing literature.

Scientific Hypothesis

The paper primarily investigates how organic food consumption depends on economic progress. To this end, we will analyze the relationship between GDP and organic food consumption using macroeconomic time series data. GDP might be viewed as an indicator of economic development, or as a proxy for disposable income. As a robustness check, disposable income is also employed as an alternative measure to verify the stability of the results.

<u>Hypothesis 1:</u>

Does higher GDP (income) lead to increased organic food consumption? Is organic food a luxury good?

Similar questions are often addressed at the microeconomic level using cross-sectional data **[35]**, and **[36]**. A positive correlation between higher income and Swedish consumers' willingness to pay for organic products was found by **[37]**. Many studies report a strong positive correlation between higher income and increased demand for organic food, treating it as a luxury good **[38]**, **[39]**, and **[40]**. From this perspective, hypothesis 1 examines the hypothesis that organic food constitutes a luxury commodity, predicated on the notion that the economic advancement of a nation facilitates its population to afford premium, healthier food.

Literature suggests that higher GDP increases environmental and health awareness, promoting organic food consumption beyond the income effect. Theoretical approaches highlight economic, social, and institutional factors to explain why and how higher GDP boosts environmental and health awareness. According to **[41]**, economic growth funds health and environmental protection, increasing demand for ecological regulations and cleaner technologies. The Environmental Kuznets Curve (EKC) was used in **[42]** to show that ecological degradation initially rises with GDP growth but decreases after a certain income level. This occurs as wealthier societies adopt cleaner technologies and increase environmental awareness. Similarly, **[43]** argues that higher relative income correlates with more significant environmental concerns. Wealthier nations prioritize ecological protection due to post-materialistic values and better education, enhancing environmental awareness. Social and institutional factors are stressed by **[44],** and it is argued that governance is crucial in translating GDP growth into ecological quality improvements.

The second goal is to examine how the 2008 economic downturn and the 2020 COVID-19 pandemic affected the relationship between organic food consumption and GDP (income). Because huge depressions are associated with substantial declines in GDP (income), the second hypothesis is as follows.

Hypothesis 2:

Does the previously mentioned mechanism:

↑GDP (income)→↑environmental and health awareness→↑organic food consumption

operate in reverse during significant economic crises:

↓GDP (income) →↓environmental and health awareness→↓organic food consumption

The third goal is to analyze long-term relations, leading to the following hypothesis:

Hypothesis 3:

Is there a long-term relationship between GDP (income) and organic food consumption?

Hypothesis 4:

How quickly is equilibrium restored after a deviation, and how does this short-run adjustment differ between crisis and non-crisis periods?

Objectives

Primary objective: The primary goal of this study is to investigate the relationship between organic food consumption and economic progress at the macroeconomic level, thereby addressing a gap in the existing literature. By utilizing time series data, the study aims to explore whether organic food consumption is influenced by a country's GDP (or income).

Secondary Objectives:

(1) Examine the impact of GDP (income) on organic food consumption:
   (a) Assess whether or not higher GDP (income) leads to increased organic food consumption.
   (b) Analyze whether organic food can be classified as a luxury good.
(2) Analyze the effects of economic downturns on organic food consumption:
   (a) Investigate whether the positive relationship between GDP (income) and organic food consumption reverses during economic crises, such as the 2008 financial crisis and the 2020 COVID-19 pandemic.
   (b) Determine the extent to which economic uncertainty in the form of crises influences consumer priorities regarding organic food.
(3) Explore the long-term relationship between GDP (income) and organic food consumption:
   (a) Assess whether a stable long-term equilibrium exists between GDP (income) and organic food demand.
   (b) Discuss implications for sustainable consumption trends.
(4) Investigate short-run dynamics and adjustment mechanisms:
   (a) Analyze how quickly organic food consumption returns to equilibrium after economic disruptions.
   (b) Compare short-run adjustments during crisis and non-crisis periods to identify potential asymmetries in consumer behavior.

MATERIAL AND METHODS

Data

This study utilizes annual data from 2000 to 2022 on the nominal per capita consumption of organic food in Germany, measured in millions of euros. We sourced the data from the FiBI database, a research institute specializing in organic food at both European and global levels. This time series was transformed from nominal to real values using the Harmonized Index of Consumer Prices (HICP) to account for inflation.

Annual data on real GDP per capita and real gross disposable income per capita, measured in millions of euros, was obtained from the Eurostat database (https://ec.europa.eu/eurostat/data/database). No transformations were applied to this time series as they were already in real terms.

Methodology

Linear regression models are symmetrical and insufficient for the second hypothesis. Thus, the second hypothesis requires a nonlinear regression model. The third and fourth hypotheses will be analyzed using the Error Correction Model (ECM) introduced by **[45]**. This model explores both long-term equilibrium and short-term dynamics. It also avoids spurious regression in time series data.

Two different methodologies will analyze hypothesis four's stability issues:

(1) Hamilton's **[46]** Markov Regime Switching (MRS) methodology,
(2) The Threshold Cointegration Model (TCM) introduced by **[47]**.

MRS approach is more suitable for our purposes as will be discussed below. Nonetheless, the TCM model is also applied as a robustness check to ensure the reliability of our results. Both approaches (MRS and TCM) allow for the endogenous modeling of crises, rather than predefining them a priori, and both frameworks incorporate nonlinearities through time-varying regression coefficients, facilitating the examination of the second hypothesis.

Transitioning from fixed to time-varying coefficients provides a more realistic representation of variable dynamics from 2000 to 2022, encompassing significant economic events such as the 2008 financial crisis and the 2020 COVID-19 crisis. The MRS and TCM methodologies are specifically designed to analyze regime shifts, making them particularly well-suited for modeling the impact of crises as regime changes.

Apart from modeling changes in regime, another reason to incorporate the MRS and TCM methodology within the ECM model is that the ECM regression assumes linear long-term and short-term relationships. Still, organic food consumption behavior might exhibit nonlinear dynamics due to changes in consumer preferences. For this reason, the ECM model is modified by nonlinear MRS and TCM methodology in this paper.

The primary advantage of the MRS and TCM models over traditional linear regression models with dummy variables (and interaction terms) is their ability to capture nonlinearities and regime shifts endogenously rather than imposing them exogenously. A linear model with dummy variables assumes that the effect of economic downturns is fixed and known a priori. MRS and TCM models allow us to endogenously identify these structural changes, meaning the model detects behavior shifts rather than imposing them based on pre-determined dates. Thus, the MRS and TCM models provide a data-driven way to detect different regimes, capturing transitions in consumer behavior endogenously rather than arbitrarily defining them in an exogenous way.

The MRS methodology offers advantages over the linear dummy variable and TCM models. Economic crises often introduce structural breaks and nonlinearities that standard linear regression models with dummy variables and TCM models cannot adequately capture as they assume that all crises have identical effects. This would oversimplify the relationship we are analyzing. In contrast, the MRS-ECM framework allows us to model smoothly varying transition probabilities, capturing the gradual nature of economic shocks rather than assuming abrupt shifts.

While MRS and TCM do add complexity, they provide substantial explanatory benefits by improving the detection of nonlinear adjustments, capturing endogenously determined regime shifts, and modeling crisis effects more flexibly than the traditional dummy variables method.

ECM, MRS, and TCM models are widely discussed and applied in the literature. The ECM model is used by **[48]** to analyze food safety concerns' impact on leafy green vegetable demand, including organic spinach. Similarly, the ECM model is applied in various empirical time series studies **[49]**, **[50]**, **[51]**, and **[52]**. The MRS methodology is prevalent in literature and applied in **[53]**, **[54]**, and **[55]**. The combination of ECM and MRS methodologies is well-documented in economic and financial literature for handling nonlinearities and model regime shifts endogenously in time series data **[56]**, **[57]**, **[58]**, and **[59]**. The TCM model has also been widely applied in various empirical studies **[60]**, **[61]**, **[62]**, and **[63]**. The influence of financial development and globalization on ecological footprint was examined by **[64]** for G7 countries using threshold cointegration. The combination of ECM and TCM model can be found in **[65]**.

MRS-ECM Model

The econometric estimation of the long-term equilibrium relationship is conducted using undifferentiated, nonstationary time series data in logarithms. The logaritmic transformation is standard in empirical economic modeling as it ensures that time series with exponential trend will transform into a series with a linear trend. Moreover, estimated coefficients can be then interpreted as elasticities, providing us with a percentage change in organic food consumption given a percentage change in GDP. To ensure the robustness of the results, we tested both raw differenced data and log-differenced data. The logarithmic transformation produced more stable results in terms of model diagnostics:

$$\ln(C_t) = \alpha_0(S_t) + \alpha_1(S_t) \cdot \ln(Y_t) + u_t,\ t = 1,2,...,T \quad (1)$$

Where:

C_t indicates the real consumption of organic food per capita in period t,

Y_t represents real GDP (or gross disposable income) per capita in period t,

u_t is a random error with white noise properties in period t,

T denotes the number of observations,

time-varying coefficients $\alpha_0(S_t)$ and $\alpha_1(S_t)$ are a function of the unobserved state variable S_t, which represents the state of the economy:

$$\alpha_0(S_t)=\begin{cases}\alpha_{0,1}, & \text{for } S_t=1,\\ \alpha_{0,2}, & \text{for } S_t=2,\end{cases}$$

$$\alpha_1(S_t)=\begin{cases}\alpha_{1,1}, & \text{for } S_t=1,\\ \alpha_{1,2}, & \text{for } S_t=2.\end{cases}$$

The variable S_t is a discrete random variable and can take two values: $S_t = 1$ for a non-crisis economy and $S_t = 2$ for a crisis. Modeling state variable S_t as unobservable implies that we do not impose a priori restrictions by determining the periods in which the economy was in a crisis. Instead, the MRS model detects crisis periods endogenously using observable data C_t, Y_t $(t = 1,2,\ldots,T)$. Development of the state variable S_t is determined by the Markov chain with transition probabilities:

$$P=\begin{bmatrix} p_{11} & 1-p_{11}\\ 1-p_{22} & p_{22}\end{bmatrix} \qquad (2)$$

where $p_{ij}=P(S_t=j\,|\,S_{t-1}=i)$ is the conditional probability that the system will be in state j at time t, given that it was in state i at time $t-1$.

The regression equation (1) represents long-term equilibrium, with estimated residuals $\hat{u}_t$ as a proxy for deviations from equilibrium. Unlike OLS methodology, the MRS model forms residuals by using regime-specific values and smoothed regime probabilities. Regime-specific residuals are calculated as follows:

$$\hat{u}_{t,1}=\ln(C_t)-\hat{\alpha}_0(S_t=1)-\hat{\alpha}_1(S_t=1)\cdot\ln(Y_t)$$
$$\hat{u}_{t,2}=\ln(C_t)-\hat{\alpha}_0(S_t=2)-\hat{\alpha}_1(S_t=2)\cdot\ln(Y_t)$$

We can only estimate the value of the state variable S_t as it is assumed to be unobserved. The smoothed estimate of regime probabilities $P(S_t = 1)$ and $P(S_t = 2)$ are calculated using Hamilton's **[46]** methodology and will be denoted by $P(S_t = 1|\Omega_T)$ and $P(S_t = 2|\Omega_T)$, respectively. The symbol Ω_T represents information set containing all the relevant information available up to time T, i.e., $\Omega_T = \{C_t, Y_t, t = 1,2,\ldots,T\}$. Residuals from the estimated MRS model (1) are then obtained according to the following relation:

$$\hat{u}_t=P(S_t=1\,|\,\Omega_T)\cdot\hat{u}_{t,1}+P(S_t=2\,|\,\Omega_T)\cdot\hat{u}_{t,2},\ t=1,2,\ldots,T \qquad (3)$$

The MRS methodology is used also to model short-run dynamics in the following form:

$$\Delta\ln(C_t)=\beta_1(S_t)\cdot\Delta\ln(Y_t)+\beta_2(S_t)\cdot\hat{u}_{t-1}+\varepsilon_t,\ t=1,2,\ldots,T \qquad (4)$$

Where: $\Delta\ln(C_t) = \ln(C_t) - \ln(C_{t-1})$
$\Delta\ln(Y_t) = \ln(Y_t) - \ln(Y_{t-1})$
$\hat{u}_{t-1}$ are lagged residuals obtained from relation (3),
ε_t is a random error with white noise properties,
coefficients $\beta_1(S_t),\beta_2(S_t)$ are function of the unobservable state variable S_t:

$$\beta_1(S_t)=\begin{cases}\beta_{1,1}, & \text{for } S_t=1,\\ \beta_{1,2}, & \text{for } S_t=2,\end{cases}$$

$$\beta_2(S_t)=\begin{cases}\beta_{2,1}, & \text{for } S_t=1,\\ \beta_{2,2}, & \text{for } S_t=2,\end{cases}$$

and the development of the state variable S_t is again determined by the Markov chain (2).

TCM Model

The TCM model econometrically estimates the long-term equilibrium relationship in the same manner as the standard ECM model:

$$\ln(C_t) = \alpha_0 + \alpha_1 \cdot \ln(Y_t) + u_t,\ t = 1,2,\ldots,T \tag{5}$$

Short-run dynamics is modeled by TCM model in the following form:

$$\Delta\ln\left(C_t\right) = \begin{cases} \beta_{1,1} \cdot \Delta\ln\left(Y_t\right) + \beta_{2,1} \cdot \tilde{u}_{t-1} + \varepsilon_t,\ \text{if } \tilde{u}_{t-1} \leq \gamma, \\ \beta_{1,2} \cdot \Delta\ln\left(Y_t\right) + \beta_{2,2} \cdot \tilde{u}_{t-1} + \varepsilon_t,\ \text{if } \tilde{u}_{t-1} > \gamma, \end{cases} \quad t = 2,\ldots,T \tag{6}$$

where $\tilde{u}_{t-1}$ are lagged residuals obtained from estimating the regression (5) by ordinary least squares,
$\beta_{1,1}$ and $\beta_{1,2}$ measure the short-run effect of GDP change on organic food consumption in two different regimes,
$\beta_{2,1}$ and $\beta_{2,2}$ measure the the speed of adjustment back to equilibrium in two different regimes,
γ is the threshold that determines when the system shifts between regimes,
ε_t is a random error with white noise properties.

Model verification

Stationarity Tests

We tested the stationarity of organic food consumption, GDP and disposable income using the Perron **[66]** test, designed for time series with dynamically identified breakpoints. The ECM model uses logarithms of the variables and their absolute differences. Consequently, the Perron test assesses the stationarity of these transformed variables and their first differences, incorporating trend and level constants for the original variables and only the level constant for the differenced data. The null hypothesis posits a unit root in the time series. Detailed findings are in Table 1.

Table 1 Results of Perron's Stationarity Test with Breakpoints in the Time Series.

Perron Test of Stationarity		**Log of Real Organic Food Consumption (per capita)**	**Log of Real GDP (per capita)**	**Log of Real Income (per capita)**
Undifferentiated Data	Test statistic	−2.70	−4.55	−3.57
	P-value	0.97	0.22	0.65
Data in First Differences	Test statistic	−4.82	−5.80	−5.26
	P-value	0.02 **	< 0.01 ***	< 0.01 ***

Source: Author's own calculations.
Note: The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels of significance, respectively.

Table 1 shows that all undifferentiated (log) data are nonstationary, with high P-values failing to reject the null hypothesis of a unit root on any meaningful level of statistical significance. However, transforming them using first differences made them stationary, as indicated by significantly lower P-values. This transformation is crucial for the ECM methodology, which relies on the stationarity of differenced series to accurately capture both the short-term dynamics and the long-term equilibrium relationships between the variables.

Cointegration Test

Applying the ECM model necessitates that the variables used $\ln(C_t)$ and $\ln(Y_t)$ are cointegrated of the first order, signifying a long-term relationship. In other words, the deviations from the long-term equilibrium $\hat{u}_t, \tilde{u}_t$ must be stationary. The stationarity was tested using the standard Augmented Dickey-Fuller (ADF) test **[67]**. Table 2 summarizes the results.

Table 2 Results of the ADF Stationarity Test for Residuals $\hat{u}_t$, $\tilde{u}_t$.

ADF Stationarity Test	Deviation $\hat{u}_t$ from Long-Run Equilibrium in MRS-ECM model		Deviation $\tilde{u}_t$ from Long-Run Equilibrium in TCM model	
	$Y_t = \log(GDP)$	$Y_t = \log(income)$	$Y_t = \log(GDP)$	$Y_t = \log(income)$
Test Statistic	−4.12	−2.26	−3.68	−3.46
P-value	0.000 ***	0.026 **	0.001 ***	0.001 ***

Source: Author's own calculations.

The null hypothesis H_0: $\hat{u}_t$ *has a unit root* is rejected even at least at 5% significance level in all the cases. Therefore, the deviation from the long-term equilibriums $\hat{u}_t, \tilde{u}_t$ are stationary.

This is a significant finding. Firstly, the stationarity of residuals $\hat{u}_t, \tilde{u}_t$ is a crucial modeling assumption. From this perspective, we have just validated this assumption as part of the econometric verification of the models. Secondly, this result already allows us to answer the Hypothesis 3:

Is there a long-term relationship between GDP (income) and organic food consumption?

The answer to this question is unequivocally YES. The reason is that the stationarity of residuals $\hat{u}_t, \tilde{u}_t$ implies that the variables $\ln(C_t)$ and $\ln(Y_t)$ are cointegrated of the first order, indicating a long-term relationship. This finding has vital implications for organic food producers and retailers as the long-run relationship between organic food consumption and economic activity confirms their confidence in the organic food market's future. It also represents valuable information for traditional food producers who would otherwise be afraid to make more significant investments in green technologies, potentially fearing that the current boom in the organic food market is only temporary.

Autocorrelation and Heteroscedasticity

Autocorrelation in time series regression models does not bias coefficient estimates but makes them inefficient, leading to incorrect standard errors, test statistics, and incorrect conclusions when testing hypotheses about model parameters.

Using the Q-statistic, we tested both models - the MRS-ECM model (4) and TCM model (6) for autocorrelation. The results of the study of Autocorrelation (AC), Partial Autocorrelation (PAC) functions, associated Q-Statistic, and the corresponding P-Value are summarized in Tables 3 and 4 for the standardized residuals.

Table 3 Autocorrelation (AC) and Partial Autocorrelation (PAC) Functions of Standardized Residuals from MRS-ECM Regression Model (4).

Lag	$Y_t = \log(GDP)$				$Y_t = \log(income)$			
	AC	PAC	Q-Stat	P-Value	AC	PAC	Q-Stat	P-Value
1	0.219	0.219	1.205	0.272	0.176	0.176	0.7785	0.378
2	−0.094	−0.15	1.441	0.487	-0.208	-0.247	1.9242	0.382
3	−0.119	−0.068	1.837	0.607	0.029	0.13	1.9483	0.583
4	−0.009	0.024	1.839	0.765	0.083	-0.005	2.1503	0.708
5	−0.092	−0.127	2.105	0.834	0.052	0.076	2.2344	0.816
6	−0.135	−0.1	2.704	0.845	-0.008	-0.023	2.2364	0.897
7	−0.121	−0.096	3.223	0.864	0.067	0.104	2.3924	0.935
8	−0.264	−0.296	5.843	0.665	-0.03	-0.097	2.4258	0.965
9	−0.202	−0.169	7.501	0.585	-0.063	0.006	2.5854	0.978
10	−0.116	−0.197	8.090	0.62	-0.147	-0.203	3.5374	0.966
11	0.216	0.131	10.34	0.5	-0.208	-0.159	5.606	0.898

Source: Author's own calculations.

Table 4 Autocorrelation (AC) and Partial Autocorrelation (PAC) Functions of Standardized Residuals from TCM Regression Model (6).

Lag	$Y_t = \log(GDP)$				$Y_t = \log(income)$			
	AC	PAC	Q-Stat	P-Value	AC	PAC	Q-Stat	P-Value
1	0.310	0.310	2.4127	0.120	0.292	0.292	2.1428	0.143
2	0.251	0.171	4.0702	0.131	0.01	-0.082	2.1453	0.342
3	0.307	0.217	6.6965	0.082	-0.133	-0.123	2.6368	0.451
4	0.118	-0.054	7.1061	0.130	-0.068	0.01	2.7737	0.596
5	0.179	0.088	8.0986	0.151	0.092	0.118	3.0366	0.694
6	-0.023	-0.185	8.1168	0.230	0.073	-0.009	3.2108	0.782
7	-0.154	-0.191	8.9525	0.256	-0.124	-0.175	3.7495	0.808
8	0.025	0.085	8.9766	0.344	-0.114	-0.002	4.2436	0.835
9	-0.180	-0.136	10.294	0.327	-0.082	-0.021	4.5134	0.874
10	-0.127	0.015	11.003	0.357	-0.121	-0.157	5.1556	0.881
11	-0.041	0.061	11.082	0.436	-0.22	-0.224	7.4771	0.759

Source: Author's own calculations.

The results in this table unequivocally indicate that the null hypothesis, which posits the absence of autocorrelation cannot be rejected at any commonly used significant level for random errors from both regressions. In other words, the data does not provide sufficient evidence to contradict the null hypothesis, thereby reinforcing its validity.

We tested for heteroscedasticity using the White **[68]** test on the MRS-ECM model (4) and on the TCM model (6), with fitted values and their squares as regressors and squared residuals as the dependent variable. The null hypothesis of no heteroscedasticity was not rejected at the 5% and 1% levels, supported by F-test and LM-test results in Table 5.

Table 5 Heteroscedasticity Test Results for White Test.

White test	Type of Test	$Y_t = \log(GDP)$		$Y_t = \log(income)$	
		Test Statistic	P-Value	Test Statistic	P-Value
MRS-ECM model (4)	F-Test	2.637	0.098	0.535	0.594
	LM-Test	4.779	0.092	1.173	0.556
TCM model (6)	F-Test	0.583	0.723	0.677	0.647
	LM-Test	3.390	0.640	3.840	0.573

Source: Author's own calculations.

RESULTS AND DISCUSSION

Parameter estimates

The MRS-ECM (4) and TCM models' parameters (6) were econometrically estimated using Eviews 9. Tables 6 and 7 summarize the results of this estimation for the baseline case $Y_t = GDP_t$. In addition to the parameter estimates, the tables also presents the P-value of the z-statistic for MRS-ECM model (t-statistic for TCM model) for each estimate, which tests its statistical significance. Furthermore, the table provides confidence intervals of 90%, 95%, and 99% for the estimated parameters, assessing the uncertainty associated with these estimates.

Table 6 Parameter Estimates for the MRS-ECM Model (4): $\Delta\ln(C_t) = \beta_1(S_t)\cdot\Delta\ln(Y_t) + \beta_2(S_t)\cdot\hat{u}_{t-1} + \varepsilon_t$, where Y_t stands for real GDP per capita.

	Estimated Parameters			
	Organic Food Consumption Elasticity to GDP		Speed of Adjustment to Equilibrium	
	$S_t = 1$	$S_t = 2$	$S_t = 1$	$S_t = 2$
	$\hat{\beta}_{1,1}$	$\hat{\beta}_{1,2}$	$\hat{\beta}_{2,1}$	$\hat{\beta}_{2,2}$
Point Estimate	4.188	2.821	−0.472	−5.897
P-Value of z-statistic	0.000 ***	0.107	0.000 ***	0.004 ***
90% Confidence Interval	(2.89,5.49)	(−0.25,5.89)	(−0.64, −0.31)	(−9.45, −2.35)
95% Confidence Interval	(2.61,5.77)	(−0.91,6.55)	(−0.67, −0.27)	(−10.21, −1.58)
99% Confidence Interval	(2.00,6.37)	(−2.33,7.98)	(−0.75, −0.20)	(−11.87, −0.07)

Source: Author's own calculations.

Table 7 Parameter Estimates for the TCM Model (6): $\Delta\ln(C_t) = \begin{cases} \beta_{1,1}\cdot\Delta\ln(Y_t) + \beta_{2,1}\cdot\tilde{u}_{t-1} + \varepsilon_t, \text{ if } \tilde{u}_{t-1} \le \gamma, \\ \beta_{1,2}\cdot\Delta\ln(Y_t) + \beta_{2,2}\cdot\tilde{u}_{t-1} + \varepsilon_t, \text{ if } \tilde{u}_{t-1} > \gamma, \end{cases}$

where Y_t stands for real GDP per capita.

	Estimated Parameters			
	Organic Food Consumption Elasticity to GDP		Speed of Adjustment to Equilibrium	
	$\tilde{u}_{t-1} \le \gamma$	$\tilde{u}_{t-1} > \gamma$	$\tilde{u}_{t-1} \le \gamma$	$\tilde{u}_{t-1} > \gamma$
	$\hat{\beta}_{1,1}$	$\hat{\beta}_{1,2}$	$\hat{\beta}_{2,1}$	$\hat{\beta}_{2,2}$
Point Estimate	4.111	2.439	−0.464	−3.378
P-Value of t-statistic	0.000 ***	0.107	0.000 ***	0.003 ***
90% Confidence Interval	(3.07,5.15)	(−0.06,4.94)	(−0.61, −0.31)	(−5.05, −1.71)
95% Confidence Interval	(2.86,5.37)	(−0.58,5.46)	(−0.65, −0.28)	(−5.40, −1.35)
99% Confidence Interval	(2.39,5.83)	(−1.70,6.58)	(−0.71, −0.22)	(−6.15, −0.61)

Source: Author's own calculations.

Discussion

The estimated values of the corresponding parameters for the two models (4) (6) are highly similar in terms of their point estimates, P-values, and confidence intervals. This consistency serves as strong evidence of the robustness of the obtained results.

Threshold parameter $\hat{\gamma}$:

The threshold parameter γ in TCM model (6) was estimated as $\hat{\gamma} = 0.12$, indicating that organic food consumption must exceed 12% of its equilibrium value to transition from the standard regime (Regime 1) to the crisis regime (Regime 2). This threshold was crossed only during two crisis periods:

(1) In 2009: Immediately following the outbreak of the global financial crisis in 2008.

(2) In 2020 and 2021: During the COVID-19 pandemic.

These results are also consistent with those obtained from the MRS-ECM model (4). As will be discussed later in the subchapter *Regime and Transition Probabilities Estimation* (see Figure 1), the estimated smoothed regime probabilities $\boldsymbol{P}(\boldsymbol{S_t} = \mathbf{2}|\boldsymbol{\Omega_t})$ for model (4) equal to 1 only in 2009 and 2020, indicating a complete shift to the crisis regime $\boldsymbol{S_t} = \mathbf{2}$ exclusively during these two periods.

Convention: In the following discussion, the results for the estimated parameters $\hat{\boldsymbol{\beta}}_{\mathbf{1,1}}$, $\hat{\boldsymbol{\beta}}_{\mathbf{1,2}}$, $\hat{\boldsymbol{\beta}}_{\mathbf{2,1}}$, $\hat{\boldsymbol{\beta}}_{\mathbf{2,2}}$ will always be presented first for the MRS-ECM model (4). The corresponding results for the TCM model (6) will then be provided immediately afterwards in brackets for comparison.

Parameter $\hat{\boldsymbol{\beta}}_{\mathbf{1,1}}$: Organic Food Consumption Elasticity to GDP in Standard Regime 1

Based on the P-values = 0.000 obtained for both models, the results are statistically significant even at the 1% level in non-crisis periods. In a non-crisis state, the Δy_t regressor positively and statistically significantly influences organic food consumption. Specifically, a 1% yearly increase in real GDP per capita triggers a 4.188% (4.111%) year-on-year surge in real organic food consumption per capita. With 99% confidence, we can assert that this increase will range between 2.00% and 6.37% (from 2.39% to 5.83%).

Let us remind the formulation of Hypothesis 1:

Does higher GDP (income) lead to increased organic food consumption? Is organic food a luxury good?

For non-crisis periods, the answer to the first part of this hypothesis is unequivocally affirmative. We reformulated it for non-crisis periods to the statistical null hypothesis $H_0: \beta_{1,1} = 0$, which was tested against the alternative hypothesis $H_1: \beta_{1,1} \neq 0$ using z-statistic (t-statistic). The null hypothesis H_0 was rejected even at the 1% significance level as P-values were equal to 0.000 for both models.

The obtained result that GDP promotes the organic food market is consistent with findings from previous research. Similar evidence is reported by **[69]**, arguing that economic growth, as reflected in a higher GDP, typically leads to increased disposable income. This increase allows consumers to prioritize health and environmental concerns, growing organic food consumption. Moreover, an increased GDP bolsters the infrastructure and market for organic food, making it more accessible to consumers. Similarly, **[70]** found that income positively influences organic food purchasing behavior, consistent with results reported in **[31]**. A study on China by **[71]** also reported similar evidence that GDP promotes organic food market. Additionally, **[72]** examined the relationship between GDP growth in Brazil and its affect on energy consumption and environmental awareness, concluding that higher GDP levels lead to greater demand for sustainability-oriented products. These findings further support the argument that economic progress is key in driving consumer preferences toward organic and environmentally friendly products.

To determine if organic food is a luxury good (defined as having an income elasticity more significant than one), we test $H_0: \beta_{1,1} = 1$ against the alternate hypothesis $H_1: \beta_{1,1} > 1$. The Wald test yields a t-statistic of 4.301 (5.204) and a P-value of 0.003 (0.000), allowing us to reject the null hypothesis even at the 1% significance level for both models. Thus, organic food is a luxury good during non-crisis periods.

The obtained result has vital implications for organic food producers and retailers. Consumers are more willing to spend extra money on organic food when the economy is doing well because they perceive it as a higher quality or more desirable product. Organic food producers and retailers can use this perception in their marketing strategies. For example, they could emphasize their products' quality, health benefits, or environmental sustainability to appeal to consumers' desire for luxury goods. They could also target their marketing towards demographics that are more likely to purchase luxury goods, such as higher-income individuals or health-conscious consumers.

Parameter $\widehat{\boldsymbol{\beta}}_{1,2}$: Organic Food Consumption Elasticity to GDP in Crisis Regime 2

The point estimate $\hat{\beta}_{1,2}$ remains positive 2.821 (2.439) during crises. However, the relationship between organic food consumption and GDP is not statistically significant, even at the 10% significance level, as P-values for both regression models are 0.107. This suggests that despite a massive GDP decline during crises, German consumers prioritize health and environmental concerns, maintaining high organic food consumption. However, the 99% confidence interval for the parameter $\beta_{1,2}$ is relatively wide ranging from $(-2.33,7.98)$ (or $(-1.70,6.58)$), indicating high degree of uncertainty regarding this coefficient.

Let us recall Hypothesis 2:

Does the mechanism:

$\uparrow GDP\ (income)$ →↑*environmental and health awareness*→↑*organic food consumption*

operate in reverse during significant economic crises:

$\downarrow GDP\ (income)$ →↓*environmental and health awareness*→↓*organic food consumption*

We reformulated this hypothesis into the following statistical hypothesis $H_0: \beta_{1,2} = 0$, which was tested against $H_1: \beta_{1,2} \neq 0$ using a z-statistic (t-statistic). The null hypothesis H_0 was not rejected even at 10% significance leves as the P-values were 0.107 for both models. This indicates that substantial GDP declines during crises do not significantly reduce organic food consumption, and consumers do not switch to cheaper conventional food during massive economic downturns. Thus, while GDP influences organic food consumption in the long term (see the discussion under Table 2 above), short-term dynamics remain uncertain. This result is supported by **[73]**, which demonstrates that economic growth drives sustainable consumption in the long run, but short-run fluctuations in GDP do not necessarily have an immediate impact in the short run.

This finding reassures organic food producers that demand for their products remains stable during massive economic downturns, reducing the risk of profit loss. This significant result of a stable organic food market resilient to crises may motivate producers to invest more in green technologies. The stability of the organic food market is also essential information for retailers, encouraging them to sign long-term contracts with organic food producers, further promoting the organic food market. It also brings critical policy implications. The German government implemented several policies during the 2008 financial crisis and the COVID-19 pandemic, including subsidies and financial assistance **[74]**, and **[75]**, public awareness campaigns **[76]**, incentives and emergency relief funds **[77]**. From this perspective, our findings suggest that these policy measures successfully supported and stabilized the organic food market during substantial economic downturns. This view is further supported by the study **[78]**, which models the effect of food subsidies on consumption dynamics and demonstrates that subsidies help sustain food demand even during economic downturns. The role of subsidies in pig production in the Czech Republic was examined by **[79]**, highlighting their impact on mitigating economic shocks within the sector.

Literature on non-economic factors such as health, taste, labeling, environmental, and ethical concerns might also help explain why consumers maintain organic food consumption even during significant GDP declines. A study by **[80]** examines the factors influencing rural consumers' purchasing behavior regarding organic food products on the Island of Arran, Scotland. Using a Structural Equation Model (SEM), the authors identify key determinants, including health consciousness, ethical concerns, environmental awareness, and trust in organic labels. The SEM model was also applied by **[70]** to analyze the determinants of Indian consumers' purchasing behavior toward organic food products. The authors identified several factors influencing consumer decisions, including health consciousness, environmental awareness, subjective norms, price sensitivity, and trust in organic certification labels.

Parameter $\widehat{\boldsymbol{\beta}}_{2,1}$: Speed of Adjustment to Equilibrium in Standard Regime 1

In the non-crisis state, the estimated coefficient $\hat{\beta}_{2,1} = -0.472$ ($\hat{\beta}_{2,1} = -0.464$) satisfies the a priori condition $\hat{\beta}_{2,1} \in (-1,0)$. This finding is further supported by all confidence intervals (90%, 95%, and 99%) for this parameter, which fall within the expected range $(-1,0)$ for both regression models. Adherence to this condition ensures that if organic food consumption was out of balance in the previous period, it only partially returns to its long-term equilibrium. The statistical significance of this adjustment mechanism, which ensures that the variables remain close to equilibrium, was demonstrated even at the 1% significance level during non-crisis periods. This is evident as the P-values for the hypothesis $H_0: \beta_{2,1} = 0$ tested against the alternate hypothesis $H_1: \beta_{2,1} \neq 0$ are 0.000 in in both regression models, confirming the strong significance of this adjustment process.

The strong significance of the adjustment process toward equilibrium is widely documented in the literature. This was also reported by **[81]**, who studied dynamics in Indian agricultural markets using threshold cointegration model. Their findings indicate that price series are well integrated, with all markets moving toward a long-run equilibrium. This supports the broader understanding that markets tend to correct deviations from equilibrium over time, reinforcing the robustness of equilibrium restoration mechanisms across different sectors and economies.

We can now partially address Hypothesis 4:
How quickly is equilibrium restored after a deviation, and how does this short-run adjustment differ between crisis and non-crisis periods?

The answer to the first part of this question is as follows: If organic food consumption exceeds its equilibrium value by 1%, the subsequent period will witness a year-on-year decrease in total organic food consumption by 0.472% (0.464%). Furthermore, with 99% confidence, we can assert that this decrease will range between 0.20% and 0.75% (0.22% and 0.71%).

The empirical literature documents that markets adjust to equilibrium at varying speeds **[82]**. While some markets exhibit rapid correction, others experience slower adjustments due to factors such as transport infrastructure, consumer behavior, and other factors. The estimated value of 0.472% (0.464%) represents the standard adjustment speed, indicating the typical rate at which deviations from equilibrium are corrected under normal market conditions.

The speed of adjustment in pork meat production and retail markets in the Czech Republic was investigated by **[83]**. The study employed a Vector Error Correction Model (VECM) to measure the equilibrium restoration speed after shocks. Their findings regarding the speed of adjustment toward equilibrium closely align with our results, as they estimated the speed of adjustment to equilibrium within their model at (-0.424).

Parameter $\hat{\beta}_{2,2}$: Speed of Adjustment to Equilibrium in Crisis Regime 2

The point estimate of the coefficient $\beta_{2,2}$, representing the speed of adjustment to equilibrium during crisis periods, is -5.897 (-3.378). The coefficient is statistically significant even at the 1% significance level, as the P-values are 0.004 (0.003) for the respective models. Its negative value implies that the economy will revert to equilibrium when it deviates from it. However, it no longer satisfies the condition $\hat{\beta}_{2,2} \in (-1,0)$. Consequently, the economy will tend to overshoot equilibrium rather than gradually return to it. This finding answers the second part of the hypothesis 4, showing that short-run dynamics differ markedly between crisis and non-crisis periods.

The study **[84]** examines short-run disequilibrium adjustment mechanisms and long-run equilibrium relationships in international stock markets. Their findings indicate that financial crises alter the degree of adjustment, making it faster during crisis periods. The paper by **[85]** examines how the European and Indonesian cocoa markets adjusted to economic crises. Their findings indicate that the speed of adjustment of short-run imbalances to long-run equilibrium varied across different economic crises in the domestic cocoa market. This further supports the notion that the speed of adjustment dynamics is crisis-dependent, with huge economic shocks influencing the rate at which markets revert to equilibrium. According to **[86]**, firms' adjustment speeds accelerate during economic crises, reflecting their increased need for financial stability. This suggests that during periods of economic distress, firms adapt more quickly to changing conditions in order to preserve liquidity, manage risks, and restore financial equilibrium, reinforcing the broader finding that adjustment mechanisms intensify during crises.

The results by **[87]** confirm that stock prices adjust to macroeconomic fundamentals more rapidly during crises than in stable periods. These findings support our research, demonstrating that crisis regimes induce faster adjustments to equilibrium, reinforcing the robustness of long-run economic relationships. Another study by **[88]** applies threshold autoregressive models to analyze how exchange rates react to oil price fluctuations. Their findings indicate that adverse shocks lead to quicker adjustments to equilibrium than positive shocks, further reinforcing our result that massive economic downturns drive faster corrections back to equilibrium. Exchange rate pass-through to inflation was studied by **[89]**, with the finding that the speed of adjustment increases during currency crises. This supports the broader conclusion that economic crises accelerate adjustment mechanisms as markets respond more rapidly to shocks to restore equilibrium.

The price transmission of the Nigerian cowpea and yam markets was studied by **[90]**. Using a Vector Error Correction Model (VECM), the researchers found that the speed of price adjustment to equilibrium varied across different periods, particularly during the food crises from 2007 to 2011. Their findings parallel our results regarding the organic food market's adjustment behavior during crisis and non-crisis periods, reinforcing the notion that adverse economic shocks in the form of crisis influence the speed of market corrections. The asymmetry in the speed of adjustment is also documented in a study by **[91]**, which applies a VECM model to analyze asymmetric price transmission in the Czech pork industry. The study finds that retail prices increase faster than they decrease, indicating an asymmetry in price transmission. This supports the broader evidence that market adjustments are not uniform, as upward and downward price movements often follow different adjustment dynamics due to market power, consumer behavior, and supply chain rigidities.

The markets for wheat and flour in Bangladesh were examined by **[92]**. Using threshold cointegration to assess asymmetries in price adjustment, the study found that price deviations from equilibrium correct at different speeds depending on the direction of the deviation. This finding aligns with the broader evidence that market adjustments are not uniform and that the correction speed may vary depending on whether the deviation is positive or negative, further supporting the concept of asymmetric market responses to economic shocks.

All these findings support our conclusion that markets respond more dynamically to deviations from equilibrium in times of financial distress, indicating that economic shocks trigger a faster correction mechanism than stable periods.

The 99% confidence interval for $\beta_{2,2}$ is (−11.87, −0.07) (or (−6.15, −0.61)), indicating some degree of uncertainty regarding the exact adjustment speed during crisis periods. Nonetheless, we can be 99% confident that the economy reverts to equilibrium during crises, as the confidence interval contains only negative values for both regression models. This confirms the presence of a significant adjustment mechanism. Moreover, the adjustment rate is likely much faster during crises compared to non-crisis periods, suggesting that deviations from equilibrium are corrected much more rapidly when the economy is distressed.

Robustness check

To assess the robustness of the results, real gross disposable income per capita was employed as an alternative to real GDP per capita in the MRS-ECM model (4) and TCM model (6). The corresponding estimation outcomes are reported in Tables 8 and 9.

Table 8 Parameter Estimates for the MRS-ECM Model (4).

	Estimated Parameters			
	Organic Food Consumption Elasticity to Income		**Speed of Adjustment to Equilibrium**	
	$S_t = 1$	$S_t = 2$	$S_t = 1$	$S_t = 2$
	$\hat{\beta}_{1,1}$	$\hat{\beta}_{1,2}$	$\hat{\beta}_{2,1}$	$\hat{\beta}_{2,2}$
Point Estimate	5.253	5.395	−0.292	−3.496
P-Value of z-statistic	0.002 ***	0.499	0.042 **	0.004 ***
90% Confidence Interval	(2.30,8.20)	(−8.58,19.37)	(−0.50, −0.08)	(−5.65, −1.34)
95% Confidence Interval	(1.67,8.84)	(−11.59,22.38)	(−0.55, −0.03)	(−6.12, −0.88)
99% Confidence Interval	(0.30,10.21)	(−18.09,28.88)	(−0.72, −0.13)	(−6.51, −0.38)

Source: Author's own calculations.

Note: $\Delta \ln(C_t) = \beta_1(S_t)\cdot\Delta\ln(Y_t) + \beta_2(S_t)\cdot\hat{u}_{t-1} + \varepsilon_t$, where Y_t stands for real income per capita.

Table 9 Parameter Estimates for the TCM Model (6).

	Estimated Parameters			
	Organic Food Consumption Elasticity to Income		Speed of Adjustment to Equilibrium	
	$\tilde{u}_{t-1} \leq \gamma$	$\tilde{u}_{t-1} > \gamma$	$\tilde{u}_{t-1} \leq \gamma$	$\tilde{u}_{t-1} > \gamma$
	$\hat{\beta}_{1,1}$	$\hat{\beta}_{1,2}$	$\hat{\beta}_{2,1}$	$\hat{\beta}_{2,2}$
Point Estimate	2.344	−0.598	−0.331	−5.314
P-Value of t-statistic	0.000 ***	0.210	0.000 ***	0.067 *
90% Confidence Interval	(1.54,3.15)	(−1.39,0.20)	(−0.43, −0.23)	(−10.04, −0.59)
95% Confidence Interval	(1.37,3.32)	(−1.56,0.37)	(−0.45, −0.21)	(−11.04, 0.41)
99% Confidence Interval	(1.01,3.68)	(−1.92,0.72)	(−0.50, −0.17)	(−13.16, 2.53)

Source: Author's own calculations.

Note: $\Delta \ln(C_t) = \begin{cases} \beta_{1,1} \cdot \Delta \ln(Y_t) + \beta_{2,1} \cdot \tilde{u}_{t-1} + \varepsilon_t, \text{ if } \tilde{u}_{t-1} \leq \gamma, \\ \beta_{1,2} \cdot \Delta \ln(Y_t) + \beta_{2,2} \cdot \tilde{u}_{t-1} + \varepsilon_t, \text{ if } \tilde{u}_{t-1} > \gamma, \end{cases}$ where Y_t stands for real income per capita.

A comparison of Tables 8 and 9 with the previously reported results in Tables 6 and 7 reveals a high degree of similarity, indicating the robustness of the findings. The estimated income elasticity of organic food consumption during non-crisis periods remains positive and statistically significant at the 1% level, with $\hat{\beta}_{1,1} = 5.253$ ($\hat{\beta}_{1,1} = 2.344$). Consistent with earlier results, the elasticity during crisis periods, $\hat{\beta}_{1,2} = 5{,}395$ ($\hat{\beta}_{1,2} = -0.598$), is not statistically significant. Regarding the speed of adjustment toward the long-run equilibrium, the estimated coefficient during non-crisis periods, $\hat{\beta}_{2,1} = -0.292$ ($\hat{\beta}_{2,1} = -0.331$), again falls within the expected interval of -1 to 0. For crisis periods, the adjustment coefficient remains below -1, with $\hat{\beta}_{2,2} = -3.496$ ($\hat{\beta}_{2,2} = -5.314$), suggesting a faster correction mechanism during economic downturns.

The estimated threshold parameter $\hat{\gamma} = 0.11$ in the TCM model (6) suggests that organic food consumption must deviate by more than 11% from its equilibrium level to trigger a transition from the standard regime (Regime 1) to the crisis regime (Regime 2). This threshold was exceeded during the same crisis periods identified previously—namely, in 2009 and 2020–2021. Furthermore, the estimated smoothed regime probabilities $P(S_t = 2|\Omega_t)$ for model (4), in which Y_t denotes real income per capita, reached a value of 1 exclusively in 2020. This indicates a complete regime shift to the crisis regime $S_t = 2$ during that year.

Summary of the main findings on formulated hypotheses

Hypothesis 1: *Is Organic Food a Luxury Good?*

The research determined that organic food is considered a luxury good in non-crisis periods. The positive dependence of organic food consumption on GDP (income) during non-crisis periods highlights the influence of economic prosperity in promoting environmental consciousness and health awareness.

Hypothesis 2: *Impact of Economic Crises on Organic Food Consumption.*

The hypothesis tested whether significant GDP (income) declines during economic crises led to decreased organic food consumption. The null hypothesis stating that GDP (income) declines do not affect organic food consumption was not rejected at any meaningful significance level. This implies that organic food consumption remains stable during economic crises and does not decrease due to substantial GDP depression. This resilience provides confidence to organic food producers and retailers regarding the stability of demand for organic products during crises.

Hypothesis 3: *Is there a long-term relationship between GDP (income) and organic food consumption?*

The analysis confirmed a significant long-term relationship between GDP (income) and organic food consumption in Germany, revealing that an increase in GDP (income) leads to higher organic food consumption over the long term. This correlation highlights that, as economic conditions improve, consumers are more likely to purchase organic food products, often priced higher than conventional alternatives.

Hypothesis 4: *How quickly is equilibrium restored after a deviation, and how does this short-run adjustment differ between crisis and non-crisis periods?*

The findings indicated that the adjustment mechanism towards long-term equilibrium significantly differs between crisis and non-crisis periods. During stable economic periods, deviations from the equilibrium are corrected only partially. In contrast, during crises such as the 2008 global economic downturn and the 2020 COVID-19 pandemic, the adjustment process might be pretty aggressive, suggesting a strong resilience of the organic food market.

Regime and transition probabilities estimation

The following Figure 1 presents a smoothed estimate of the probabilities for the individual regimes $S_t = 1$ and $S_t = 2$. These estimates are derived from the MRS-ECM regression model (4), utilizing all the information available in the entire dataset.

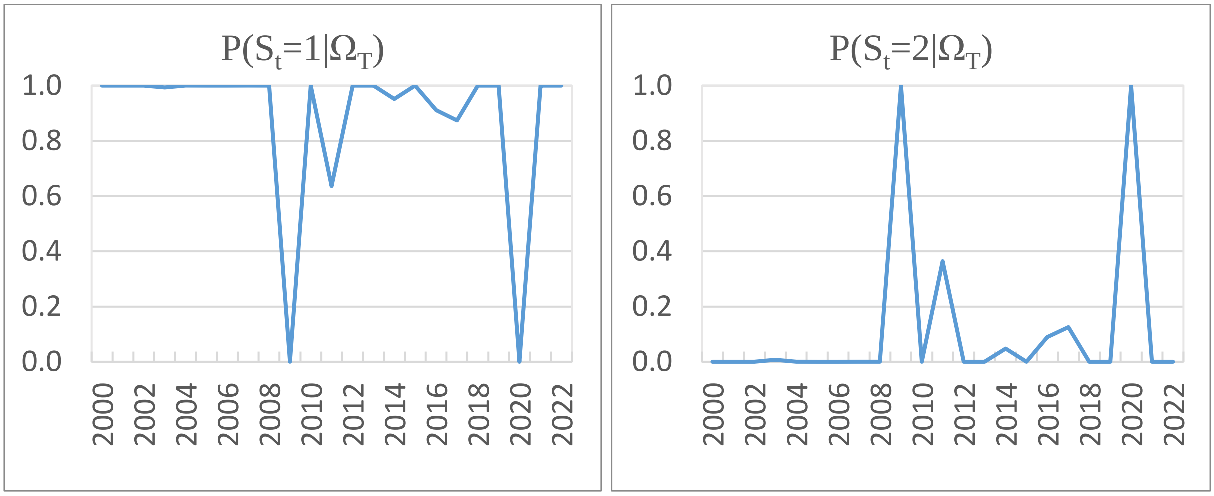

Figure 1 Estimated Smoothed Probabilities $P(S_t = 1|\Omega_T)$, $P(S_t = 2|\Omega_T)$ for Short-Run Regression Model (4).

The graph shows that the MRS-ECM model (4) identifies regime changes around the 2009 and 2020 crises. These regime changes were short-lived, with the crisis $S_t = 2$ lasts only one year in each case. This brief duration reflects that the most severe phase of a crisis occurs at its onset. Similar crisis durations are reported in the literature. The MRS-GARCH model was used by **[54]** to analyze the Ibovespa (Brazilian stock exchange) during the 2008 and COVID-19 crises, finding high-volatility periods lasting about three months in 2008 and two months in 2020. According to **[93]**, the 2008 financial crisis and COVID-19 pandemic significantly negatively impacted China's GDP, with recovery expected in about a year.

As previously noted, the TCM model (6) identified the economy as being in crisis regime 2 during the years 2009, 2020, and 2021 (see the discussion of the threshold parameter $\hat{\gamma}$ above). Thus, not only are the parameter estimates analyzed models (4) (6) highly similar, but they also exhibit consistency in identifying the economic regime, further reinforcing the robustness of the obtained results.

The MRS-ECM model (4) offers greater flexibility than the TCM model (6), as Markov-Switching methodology allows smooth probabilities $P(S_t = 2|\Omega_T)$ to change gradually rather than abruptly. The MRS modeling approach provides a nuanced analysis of how the impact of the 2008 global financial crisis differs from that of the COVID-19 pandemic, as the dynamics of $P(S_t = 2|\Omega_T)$ may vary across these crises.

Additionally, the MRS approach can also distinguish between how quickly a crisis impacts organic food market, and how quickly the effects of the crisis subside, since the dynamics of $P(S_t = 2|\Omega_T)$ might differ in the initial and final phases of a crisis.

In contrast, the TCM methodology lacks this flexibility. Regime shifts always occur abruptly in the TCM model, and they are determined strictly by whether the deviation from equilibrium $\tilde{u}_{t-1}$ economy crosses the threshold. This inherent rigidity prevents the TCM model from capturing gradual transitions between economic regimes.

Nonetheless, the results obtained from estimating smoothed probabilities $P(S_t = 2|\Omega_T)$ within the MRS-ECM framework demonstrate that the regime change was abrupt during the 2008 global financial crisis and the 2020 COVID-19 pandemic. The estimated probability of the crisis regime $P(S_t = 2|\Omega_T)$ for MRS-ECM model (4) changed abruptly: (1) during the 2008 crisis from 0 in 2008 to 1 in 2009, followed by an immediate reversal back to 0 in 2010, (2) during the COVID-19 pandemic from 0 in 2019 to 1 in 2020, followed by an immediate reversal back to 0 in 2021. These results indicate that: (1) both economic crises had a sudden and abrupt impact on the organic food market, (2) the effects of both crises were short-lived, lasting only one year, and (3) the impact of both crises disappeared abruptly rather than fading gradually.

It is crucial to interpret these results correctly. When we state that the effects of both crises were short-lived and disappeared abruptly, we specifically refer to the probability of being in the crisis regime $P(S_t = 2|\Omega_T)$, which was equal to 1 only in 2009 and 2020 and then abruptly switched back to 0 in the subsequent years, 2010 and 2021. However, this does not imply that the deviation from equilibrium (either $\tilde{u}_t$ or $\hat{u}_t$) also switched abruptly back to 0 in 2010 and 2021. In fact, the estimated deviations from equilibrium in those years were $\tilde{u}_{2010} = 0.06$, $\hat{u}_{2010} = 0.05$, $\tilde{u}_{2021} = 0.20, \hat{u}_{2021} = 0.17$. These values suggest that while the economy transitioned out of the crisis regime in 2021, the organic food market remained far away from its long-run equilibrium that year. This indicates that although the probability of being in the crisis regime $P(S_t = 2|\Omega_T)$ returned to 0, the adjustment process toward equilibrium was still ongoing, and the market had not yet fully stabilized.

For the long-run relationship (1), the regression model also confirmed the presence of a break in 2009 and 2020-2021. Moreover, estimated smoothed probabilities for this long-run regression are practically the same as for the short-run dynamics model (4). This is illustrated in Figure 2.

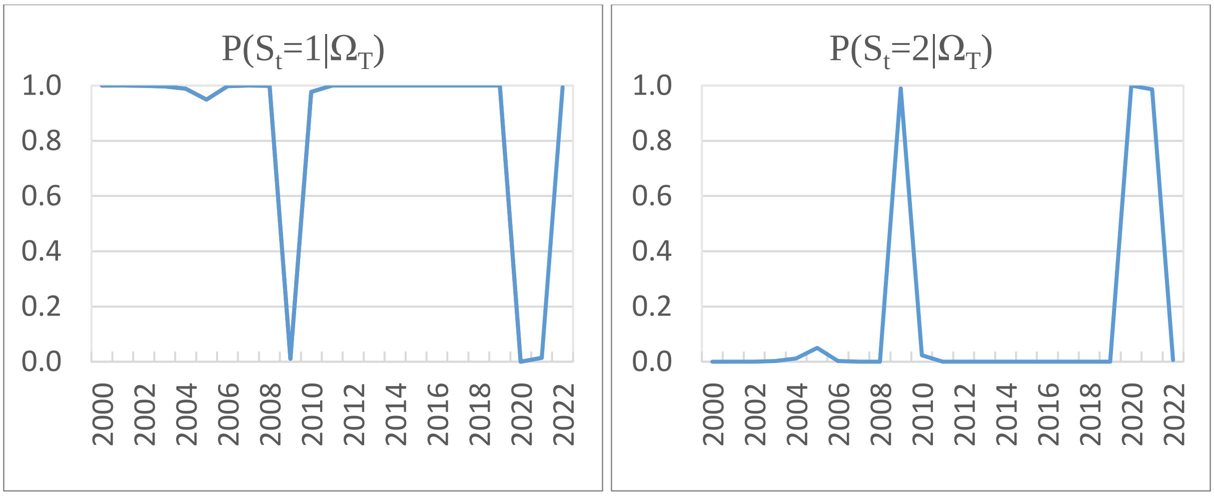

Figure 2 Estimated Smoothed Probabilities $P(S_t = 1|\Omega_T)$, $P(S_t = 2|\Omega_T)$ for Long-Run Regression Model (1).

The transition probabilities matrix (2) for the regression model (4) was estimated as follows:

$$\hat{P} = \begin{bmatrix} 0.86 & 0.14 \\ 1 & 0 \end{bmatrix}.$$

If the economy is currently in the non-crisis regime ($S_t = 1$), it will remain in this regime in the subsequent year with a probability of 0.86, and transition to the crisis regime ($S_t = 2$) with a probability of 0.14. Conversely, if the economy is currently in the crisis regime ($S_t = 2$), it will invariably transition to the non-crisis regime ($S_t = 1$) with a probability of 1 in the following year.

Based on these probabilities, the expected duration of the non-crisis regime ($S_t = 1$) is approximately 7.15 years. This suggests that, on average, once the economy enters a non-crisis state, it tends to remain in that state for about seven years before transitioning to a crisis state. The expected duration of the crisis regime ($S_t = 2$) is only one year, reflecting its role as the most challenging phase at the crisis onset.

Policy implications

The study's findings have significant implications for policymakers, organic food producers, and retailers. Firstly, organic food producers and retailers can utilize the result that organic food is a luxury good during a non-crisis state of the economy and tailor their marketing strategies more effectively. Secondly, the finding that organic food consumption remains stable during crises suggests that government subsidies, consumer trust, and brand loyalty may play vital roles in maintaining market stability. Thus, (i) producers can invest confidently in organic farming and without fearing a drop in demand, (ii) retailers may consider signing long-term contracts with organic food producers, further promoting the organic food market's growth, (iii) the German government's policies during the 2008 financial crisis and the COVID-19 pandemic, such as subsidies, financial assistance, and public awareness campaigns, were effective in stabilizing the organic food market. Thirdly, the long-run relationship between organic food consumption and a country's economic activity level further confirms producers' and retailers' confidence in the organic food market's future perspectives. It also motivates traditional food producers to invest in green technologies, alleviating fears that the current organic food market boom is temporary.

Further research

The study represents a significant advancement in understanding the intricate dynamics of organic food consumption during economic crises. However, further research is required to fully comprehend this topic's complexities and formulate effective strategies for promoting organic food consumption. The empirical investigation conducted in this paper was confined solely to the German economy. The significance of the German economy stems from its status as Europe's largest organic food market. Nevertheless, future research could undertake a comparative cross-country analysis to obtain a more comprehensive understanding and robust results. It would be especially intriguing to compare economies with varying levels of economic development and cultural attitudes toward organic food. Future research could also explore the specific factors contributing to the resilience of organic food consumption during crises, providing a more nuanced understanding of consumer behavior in this market.

This study applied the MRS-ECM and TCM model to analyze consumer behavior in the organic food market. However, alternative econometric methodologies could also be considered. For instance, Structural Vector Autoregression (SVAR) models are beneficial for capturing dynamic interactions among multiple variables and allow for the identification of shocks using structural restrictions. However, standard SVAR models do not explicitly account for regime shifts unless combined with additional nonlinear specifications. A Markov-switching SVAR model could be explored as a potential alternative to address this limitation. This approach would allow for integrating other variables and structural shocks while preserving the regime-switching dynamics, offering a more comprehensive framework for analyzing the interplay between economic shocks and organic food market behavior.

Another potential avenue for future research involves several key directions. First, the integration of additional behavioral economic theories such as the Environmental Kuznets Curve, Prospect Theory, or the Bounded Rationality Model. Second, future studies may benefit from the incorporation of broader economic indicators, including household debt levels and employment trends, to better contextualize consumer behavior within macroeconomic conditions. Third, combining survey-based micro-level data with macroeconomic models presents an opportunity to enhance the analytical robustness and explanatory power of such investigations.

CONCLUSION

The paper aimed to analyze how economic activity affects organic food consumption in Germany using time series macroeconomic data, focusing on the effects of the 2008 and 2020 crises. Empirical literature analyzing the organic market on a macroeconomic level using time series data is practically missing, making this study a valuable contribution. This research extends the existing literature by utilizing aggregate indicators in Germany, Europe's largest organic market. It enhances the understanding of consumer behavior and the resilience of the organic food market during crises, which is crucial for producers, retailers, and policymakers. Moreover, both long-run equilibrium and short-run dynamics were analyzed, with a modified Error Correction Model incorporating breakpoint analysis modeled by both Markov Regime Switching methodology and Threshold Cointegration approach. This comprehensive approach offers new robust findings regarding the relationships between organic food consumption and a country's economic activity level, contributing significantly to the understanding of the organic market at a macroeconomic level.

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